University of Alberta

Optimizing Network Performance with Changing and Uncertain Traffic Demands

by

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Abstract

Communication networks are becoming increasingly important. Because of the growing demands on communication networks, it is critical to optimize network performance. However, the traffic demands on networks, including both the Internet and wireless networks, are usually changing and uncertain, which makes optimization of network performance a challenging problem. In this thesis, robust routing schemes are investigated to optimize network performance with changing and uncertain traffic demands for both the Internet and wireless networks.

For the Internet, an efficient and deployable multipath implementation of demand-oblivious routing is investigated to optimize network performance without accurate knowledge of traffic demands. Extensive numerical and simulation studies show the excellent performance of the multipath implementation under varying traffic demands, link failures and an adversary attack.

For wireless networks, a traffic-oblivious energy-aware routing scheme is studied. Numerical studies show that oblivious routing can achieve the performance close to what an oracle can achieve, especially for the case where there is a single sink to receive messages. For both the Internet and wireless networks, more accurate knowledge of traffic demands implies better performance of oblivious routing, hence resulting in better network performance.

This thesis research has advanced the state-of-the-art of research for both the Internet and wireless networks, by designing an efficient and deployable implementation of demand-oblivious routing in the Internet and by relaxing the assumption of the priori knowledge of traffic demands in optimizing the energy efficiency of wireless networks.

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[1] I choose not to list all the people who were helpful to me during my PhD study, since the list would be too long. If you wonder, "Why my name is not here?", I owe you a big "Thank you!".

To my Mom.

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Chapter 1

Introduction

Networks are becoming more and more important, e.g., the Internet and cellular networks are already indispensable to us. New applications and services are emerging, like video conferencing on the Internet and environmental monitoring with wireless sensor networks, which pose more stringent requirements on network resources.

With scarce network resources, the optimization of network performance is an important challenge for network researchers and practitioners. Bandwidth is the resource for the Internet. The percentage of link bandwidth usage, link utilization, is a standard performance metric. In a wireless network, resources include frequency spectrum (bandwidth) and energy supply. Energy efficiency, an indicator of how fast energy is consumed, is a paramount issue in wireless networks with energy constraints. A strategy for resource allocation may take the form of a routing in the Internet, possibly combined with scheduling in wireless networks. Briefly, a routing specifies which route(s) the traffic will flow on and how much traffic a route will accommodate. In wireless networks in which time is divided into slots, a scheduling specifies the time slot(s) during which a transmitter can be active. It is desirable to design strategies for resource allocation to achieve optimal network performance, such as that in terms of link utilization or energy efficiency.

Such network performance optimization falls into the general research area of traffic engineering, which is usually applied to the Internet. Quoted from [9], "Traffic engineering is concerned with performance optimization of operational networks. In general, it encompasses the application of technology and scientific principles to the measurement, modeling, characterization, and control of Internet traffic, and the application of such knowledge and techniques to achieve specific performance objectives."

1.1 Problem Definition

When accurate knowledge of the traffic demands is available, optimization of network performance like link utilization in the Internet and energy efficiency in wireless networks can be solved by the well-known linear programming (LP) network flow theory [4]. The traffic demand may be known a priori in some applications, such as in a wireless sensor network in which sensors periodically report weather information. However, in many cases, network traffic demands are changing and uncertain.

It is difficult to obtain an accurate estimate of the traffic demand in the scenario of the Internet [8, 13, 70], even though a large amount of measurement data is available. To estimate the traffic demand accurately is likely to be difficult in multihop wireless networks. Recently researchers study traffic characterization in wireless networks, mainly in a wireless LAN (Local Area Network), e.g. Meng et al. [44]. Even if an estimate is accurate, it is in a statistical sense, which means there is an error margin with the estimation. Some wireless networks may be designed with the expected traffic demand in mind, for example, in a sensor network where temperature information is reported periodically. However, in some cases, there are unexpected or unscheduled events. In the sensor network example, the sensors may also need to report temperature changes exceeding a certain threshold, which may not be predictable. Furthermore, the actual traffic may deviate from the expectation. Therefore, it is desirable to allow for errors, deviation and uncertainties in traffic prediction when designing a routing scheme. On the other hand, approximate knowledge of traffic demands is made available by the recent great progress in traffic estimation, e.g. [13, 18, 32, 43, 61, 70, 71]. Thus, it is desirable to take advantage of the approximate knowledge of traffic demands where it is available.

In this thesis, the problem of designing routing schemes robust to changing and uncertain traffic demands is investigated for both the Internet and wireless networks. Although *oblivious routing needs centralized computation* based on network topology information, the resultant routing is fully distributed, since no further network information is needed.[1]

For the Internet, Applegate and Cohen [8] investigate demand-oblivious routing to optimize network performance with respect to link utilization without accurate knowledge of traffic demands. However, it is non-trivial to implement the routing scheme in [8], since a large number of routes may be required and routing loops may be formed. In this thesis, first a method is developed to dramatically reduce the number of paths and path lengths of the demand-oblivious routing [8]. Furthermore, an efficient and deployable implementation of the demand-oblivious routing in [8] is studied, so that it advances this research to a more practical stage to improve the performance of the Internet.

For wireless networks, traffic-oblivious energy-aware routing is studied, which relaxes the assumption of accurate a priori knowledge of traffic demands when optimizing energy efficiency in most previous work. In wireless networks, when interference is present, a routing may not be achievable. How to guarantee schedulability of a routing given traffic demands is

[1]Section 4.5 discusses implementation and deployment issues for the case of the Internet, and Section 6.7 discusses implementation issues for the case of wireless networks.

studied in previous work, e.g., [30]. Based on this previous work, schedulability of a traffic-oblivious routing is guaranteed in an interference-limited setting. Reliable transmission is also considered when links are lossy for the traffic-oblivious routing.

1.2 Research Methodology

Two types of networks, the Internet and wireless networks, are studied. However, there is a unified approach to the research problems: a networking problem is formulated as an LP optimization problem on an abstract model, and extensive numerical and simulation studies are used for performance evaluation to complement the modeling and analysis. LP network flow theory [4] is used for both the link utilization problem in the Internet and the energy efficiency problem in wireless networks.

1.3 Contribution of Research

This thesis has advanced the state-of-the-art of research for both the Internet and wireless networks, with respect to optimizing link utilization and energy efficiency with changing and uncertain traffic demands.

Contribution for research in the Internet. This is the first investigation of a feasible implementation of demand-oblivious routing [8], so that only a small number of routes is needed and routing loops are eliminated. MORE, a multipath implementation of [8], is formulated as a polynomial sized LP. Several path selection methods are designed, including a method which dramatically reduces the number of paths and path lengths of the demand-oblivious routing [8]. Extensive numerical experiments and simulation show the excellent performance of MORE under varying traffic demands, link failures and an adversary attack. Its performance is excellent even with a 100% error in traffic estimation. This opens the door for a viable deployment of oblivious routing, thus providing an intra-domain traffic engineering technique robust to changing and uncertain traffic demands. MORE is a promising option for the Internet traffic engineering. Portions of this work have been published in [36].

Contribution for research in wireless networks. A traffic-oblivious, energy-aware routing scheme is formulated as a polynomial sized LP. It does not need ongoing network information collection, guarantees schedulability in an interference-limited scenario, and provides reliable transmission in a lossy environment. It relaxes the assumption of accurate knowledge on traffic demands required in previous work on energy efficiency, e.g. [14]. The experiments show that the oblivious routing can achieve performance close to what an oracle can achieve. The performance is particularly good when there is a single sink to receive messages. This has made a first step in designing a traffic-oblivious energy-aware routing framework in multihop wireless networks. Portions of this work have been published in [35, 38].

This thesis research does have limitations, including linearity for optimization problem formulation, scalability of LP formulations, implementation issues, multipath selection methods for MORE, and the effect of traffic burstiness for design and evaluation of MORE, as will be discussed in Section 7.2.

1.4 Outline of Thesis

The thesis naturally breaks into two parts: one for the Internet and another for wireless networks. In each part, before the thesis work is presented, background material is discussed. Discussions about related work are placed where they fit.

Background materials for network flow are presented in Chapter 2, in which, Section 2.1 and Section 2.2 are for both the Internet and wireless networks. In Chapter 3, the approach to improve the quality of routing of demand-oblivious routing in [8] is presented. In Chapter 4, an efficient and deployable implementation of demand-oblivious routing [8] is investigated. Background material for the research on wireless networks is presented in Chapter 5. In Chapter 6, traffic-oblivious energy-aware routing in wireless networks is studied. Then conclusions are drawn and limitations and future work of the research are discussed. Chapter 3 and Chapter 4 make contributions to research in the Internet. Chapter 5 and Chapter 6 make contributions to research in wireless networks.

Chapter 2

Background: Network Flow Problems

Network flow theory [4] deals with problems of shipping one or more commodities through a network, to optimize a certain objective, e.g., minimizing the shipment cost or maximizing the amount of flow, subject to certain constraints, e.g., flow conservation and link capacity constraints. The traffic for each Origin-Destination (OD) pair is treated as a commodity. The problems are usually multi-commodity problems [4].

A traffic matrix (TM) provides the amount of traffic between each OD pair over a certain time interval. Given the traffic matrix, the minimax link utilization can be solved as a multicommodity flow linear programming problem [45].

Preliminaries for linear programing will be presented. After the introduction of definitions of a routing and a flow, linear programming formulations for the problem of minimax link utilization will be presented. Then oblivious routing will be discussed.

The notation follows. A network is represented by a graph $G = (V, E)$, where V is the set of nodes and E is the set of edges. Each edge (u, v) has a capacity $c(u, v)$, or $c(e)$ for edge e. As well, the capacity of link l is denoted as $c(l)$. Use $in(k)$ and $out(k)$ to denote edges "entering" or "leaving" node k respectively.

2.1 Preliminaries: Linear Programming

Linear programming (LP) deals with optimization problems to minimize or maximize a linear objective function subject to linear constraints, e.g., [12, 49]. A linear program may be in the following form, with x's as variables,

$$
\begin{array}{llcccccc}
\text{minimize} & c_1x_1 & + & c_2x_2 & +\ldots+ & c_nx_n & & \\
\text{subject to} & a_{11}x_1 & + & a_{12}x_2 & +\ldots+ & a_{1n}x_n & \geq b_1 & \\
 & a_{21}x_1 & + & a_{22}x_2 & +\ldots+ & a_{2n}x_n & \geq b_2 & \\
 & \cdot & & \cdot & & \cdot & \cdot & \\
 & \cdot & & \cdot & & \cdot & \cdot & \\
 & a_{m1}x_1 & + & a_{m2}x_2 & +\ldots+ & a_{mn}x_n & \geq b_m & \\
 & x_1 & , & x_2 & ,\ldots, & x_n & \geq 0 &
\end{array} \tag{2.1}
$$

An assignment of x's that satisfies all the constraints is a *feasible* solution. A feasible solution that minimizes the objective function is an *optimal* solution. Let $\mathbf{c} = (c_1, c_2, ..., c_n)$, $\mathbf{x} = (x_1, x_2, ..., x_n)^T$, $\mathbf{b} = (b_1, b_2, ..., b_n)^T$, and A be a $m \times n$ matrix with (i, j) entry a_{ij}. We have linear program (2.1) in matrix form,

$$
\begin{array}{lccc}
\text{minimize} & \mathbf{cx} & & \\
\text{subject to} & \mathbf{Ax} & \geq & \mathbf{b} \\
 & \mathbf{x} & \geq & \mathbf{0}
\end{array} \tag{2.2}
$$

An associated linear program with $\mathbf{y}$ as variables follows,

$$
\begin{array}{lccc}
\text{maximize} & \mathbf{yb} & & \\
\text{subject to} & \mathbf{yA} & \leq & \mathbf{c} \\
 & \mathbf{y} & \geq & \mathbf{0}
\end{array} \tag{2.3}
$$

LP (2.2) is the *primal* LP corresponding to the *dual* LP (2.3).

LP duality theorem. The primal LP has an optimal solution if and only if the dual LP has an optimal solution. Moreover, if $\mathbf{x}$ and $\mathbf{y}$ are optimal solutions for primal LP (2.2) and dual LP (2.3) respectively, then,

$$\mathbf{cx} = \mathbf{yb}.$$

CPLEX [1] is used to solve LP programs in numerical studies.

2.2 Routing and Flow

An entry in a traffic matrix d_{ij} denotes the amount of traffic of OD pair $i \rightarrow j$. A routing $f_{ij}(e)$ specifies the fraction of traffic demand d_{ij} on edge e. Flow $g_{ij}(e)$ denotes the amount of traffic for OD pair $i \rightarrow j$ on edge e, i.e., $g_{ij}(e) = d_{ij}f_{ij}(e)$. The definitions in [8] are adopted here.

A routing specifies how to route the traffic between each OD pair across a given network. Open Shortest Path First Protocol (OSPF) and Intermediate System to Intermediate System (IS-IS), two popular Internet routing protocols, follow a destination-based evenly-split approach. The MultiProtocol Label Switching (MPLS) architecture allows for more flexible routing. Both OSPF/IS-IS and MPLS can take advantage of path diversity. OSPF/IS-IS distributes traffic evenly on multiple paths with equal cost. MPLS may support arbitrary routing fractions over multiple paths. A routing by the definition given above is applicable to MPLS, which is widely deployed by ISPs.

Figure 2.1 presents an example routing for illustration. For this example, the vector $\langle f_{i_1,j_1}(e), f_{i_2,j_2}(e)\rangle$ on each edge e specifies the routing. For example, in Figure 2.1, $\langle 1,0\rangle$ on edge (i_1, A) specifies that 100% of the traffic for OD pair $i_1 \rightarrow j_1$ travels edge (i_1, A); while no traffic of $i_2 \rightarrow j_2$ on (i_1, A). The vector $\langle .2, .4\rangle$ on edge (A, B) specifies 20% of the traffic of $i_1 \rightarrow j_1$ and 40% of the traffic of $i_2 \rightarrow j_2$ travel edge (A, B). For conservation constraints, the routing fractions entering a node must be equal to the routing fractions leaving a node. For example, for OD pair $i_1 \rightarrow j_1$, the routing fractions entering node A, $1.0 + 0.0 = 1.0$, is equal to the routing fractions leaving node A, $0.2 + 0.8 = 1.0$.

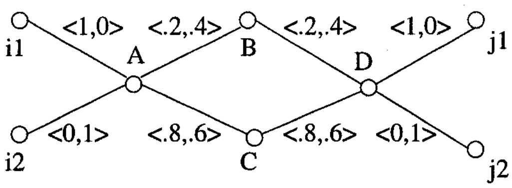


Figure 2.1: An Example: a routing for a topology

Routing $\mathbf{f}$, which specifies $f_{ij}(e)$ for every OD pair $i \rightarrow j$ and every edge e, is defined as:

$$\begin{cases} \forall \text{ pairs } i \rightarrow j: \sum\limits_{e \in out(i)} f_{ij}(e) - \sum\limits_{e \in in(i)} f_{ij}(e) = 1 \\ \forall \text{ pairs } i \rightarrow j, \forall \text{ nodes } k \neq i,j: \sum\limits_{e \in out(k)} f_{ij}(e) - \sum\limits_{e \in in(k)} f_{ij}(e) = 0 \\ \forall \text{ pairs } i \rightarrow j, \forall \text{ edges } e: f_{ij}(e) \geq 0 \end{cases} \tag{2.4}$$

From the above, we can derive the constraint,

$$\forall \text{ pairs } i \rightarrow j: \sum_{e \in in(j)} f_{ij}(e) - \sum_{e \in out(j)} f_{ij}(e) = 1.$$

Similarly, flow $\mathbf{g}$ is defined as,

$$\begin{cases} \forall \text{ pairs } i \rightarrow j: \sum\limits_{e \in in(j)} g_{ij}(e) - \sum\limits_{e \in out(j)} g_{ij}(e) = d_{ij} \\ \forall \text{ pairs } i \rightarrow j, k \neq i,j: \sum\limits_{e \in out(k)} g_{ij}(e) - \sum\limits_{e \in in(k)} g_{ij}(e) = 0 \\ \forall \text{ pairs } i \rightarrow j, \forall \text{ edges } e: g_{ij}(e) \geq 0 \\ \forall \text{ pairs } i \rightarrow j: d_{ij} \geq 0 \end{cases} \tag{2.5}$$

From above, we can derive the constraint,

$$\forall \text{ pairs } i \rightarrow j: \sum_{e \in out(i)} g_{ij}(e) - \sum_{e \in in(i)} g_{ij}(e) = d_{ij}$$

In network flow, the link capacity constraint (2.6) stipulates that the flow on a link cannot exceed the link capacity, and the flow non-negative constraint (2.7) stipulates that the flow on a link cannot be negative.

$$\forall \text{ edges } e: \quad \sum_{i,j} g_{ij}(e) \leq c(e) \tag{2.6}$$

$$\forall \text{ pairs } i \rightarrow j, \forall \text{ edges } e: \quad g_{ij}(e) \geq 0 \tag{2.7}$$

2.3 Link Utilization in the Internet

For a given routing $\mathbf{f}$ and a given traffic demand $\mathbf{tm}$, the maximum link utilization (MLU) measures the goodness of the routing, i.e., the lower the MLU, the better the routing:

$$\text{MLU}(\mathbf{tm}, \mathbf{f}) = \max_{e \in E} \sum_{i,j} d_{ij} f_{ij}(e)/c(e)$$

Given a TM $\mathbf{tm}$, the *optimal routing* minimizes the maximum link utilization:

$$\text{OPTU}(\mathbf{tm}) = \min_{f} \max_{e \in E} \sum_{i,j} d_{ij} f_{ij}(e)/c(e)$$

Equivalently, the LP formulation follows, with routing $\mathbf{f}$ and η as the variable,

$$\begin{aligned} &\min_{\eta, f} \eta \\ &f_{ij}(e) \text{ is a routing} \\ &\forall \text{ edges } e \in E : \sum_{i,j} d_{ij} f_{ij}(e)/c(e) \leq \eta \end{aligned} \tag{2.8}$$

2.4 Oblivious Routing

It is non-trivial to measure or estimate traffic demands accurately [13], [70]. Designing a routing that is robust to changing and uncertain traffic is desirable [8]. The oblivious routing problem is to design a routing that achieves close to the optimal performance, with no or only approximate knowledge of the traffic pattern. Performance evaluation of an oblivious routing scheme follows a competitive analysis framework. Briefly, the oblivious performance ratio measures how far a routing is from the optimal with respect to all possible traffic matrices.

2.4.1 Related Work

A brief review of the work on oblivious routing follows. Räcke [53] investigates oblivious routing on general symmetric networks. This work is viewed as a breakthrough, since previous work solves oblivious routing only on topologies with particular structures. Azar et. al. [10] show that an optimal oblivious routing can be computed by an LP with a polynomial number of variables, but infinitely many constraints on general networks. Its polynomial complexity is established using the Ellipsoid method [40]. Applegate and Cohen [8] develop LP models of polynomial sizes to solve the oblivious routing problem in the context of the Internet. They investigate the performance of the oblivious routing on Rocketfuel topologies [62]. They show that the oblivious routing achieves good performance: an oblivious ratio of less than 2 or even lower with fairly approximate knowledge of the traffic pattern. Applegate et al. [7] study demand oblivious restoration strategies.

2.4.2 Competitive Analysis

The routing computed by LP (2.8) does not guarantee performance for other traffic matrices. Applegate and Cohen [8] developed LP models to compute the optimal routing that achieves minimax link utilization with a weak assumption on the traffic pattern. First the metric of competitive ratio is introduced that follows the competitive analysis [8, 50].

For a given routing **f**, a given traffic matrix **tm**, the *competitive ratio* is defined as the ratio of the maximum link utilization of the routing **f** on the traffic matrix **tm** to the maximum link utilization of the optimal routing for **tm**. The competitive ratio measures how far routing **f** is from the optimal routing for traffic matrix **tm**.

$$\mathrm{CR}(\mathbf{f}, \{\mathbf{tm}\}) = \frac{\mathrm{MLU}(\mathbf{tm}, \mathbf{f})}{\mathrm{OPTU}(\mathbf{tm})} \tag{2.9}$$

The competitive ratio is usually greater than 1. It is equal to 1 only when the routing **f** is an optimal routing for **tm**. When we are considering a set of traffic matrices **TM**, the competitive ratio of a routing **f** is defined as

$$\mathrm{CR}(\mathbf{f}, \mathbf{TM}) = \max_{\mathbf{tm} \in \mathbf{TM}} \mathrm{CR}(\mathbf{f}, \{\mathbf{tm}\}) \tag{2.10}$$

The competitive ratio with respect to a set of traffic matrices is usually strictly greater than 1, since a single routing usually can't optimize link utilization over the set of traffic matrices.

When set **TM** includes all possible traffic matrices, $\mathrm{CR}(\mathbf{f}, \mathbf{TM})$ is referred to as the *oblivious competitive ratio* of the routing **f**. This is the worst competitive ratio the routing **f** achieves with respect to all traffic matrices. An *optimal oblivious routing* is the routing that minimizes the oblivious competitive ratio. Its oblivious ratio is the *optimal oblivious ratio* of the network.

Suppose there is an oracle that knows the instant traffic matrix **tm** and computes its optimal routing with link utilization u. The link utilization of the optimal oblivious routing for **tm** is guaranteed to be within $[u, r * u]$, where r is the oblivious ratio. It may achieve lower link utilization than $r * u$ for the particular traffic matrix **tm**. The oblivious routing guarantees the performance of what an oracle can achieve multiplied by the oblivious ratio for all traffic matrices.

Table 2.1 presents an example to illustrate the performance metric of competitive ratio. Suppose all other TMs have $\mathrm{CR}(\mathbf{f}, \{\mathbf{tm}\})$ less than 1.5. Then, $\max_{\mathbf{tm} \in \mathbf{TM}} \mathrm{CR}(\mathbf{f}, \{\mathbf{tm}\})$, or oblivious ratio, is 1.5. Table 2.1 also shows that for some TM, the performance ratio can be lower than 1.5, e.g., for TM_3, the ratio is 1.2. This shows that the oblivious routing **f** can perform better than the oblivious ratio predicts.

	TM_1	TM_2	TM_3	...	TM_∞
MLU(**tm**, {**f**})	0.7	0.6	0.6		
OPTU(**tm**)	0.5	0.4	0.5		
CR(**f**, {**tm**})	1.4	1.5	1.2		
$\max_{\mathbf{tm} \in \mathbf{TM}}$ CR(**f**, {**tm**})			**1.5**		

Table 2.1: Example: oblivious ratio for routing **f**

2.5 Summary

Background materials for network flow are presented in this chapter. Preliminaries for linear programming in Section 2.1 and discussions and definitions for routing and flow in Section 2.2 are for both the Internet and wireless networks. Link utilization in the Internet is discussed in Section 2.3, and oblivious routing is discussed in Section 2.4. The discussion about competitive analysis in Section 2.4.2 for link utilization in the Internet has similar flavor to that for energy utilization in Section 5.3.4 for wireless networks.

Chapter 3

Balancing Oblivious Ratio and Quality of Routing

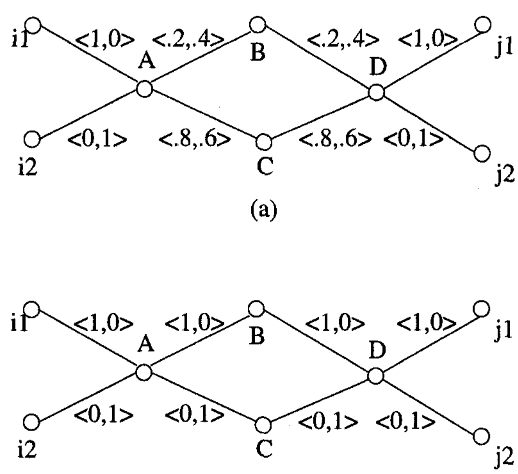
Applegate and Cohen [8] design demand-oblivious routing schemes that achieve low oblivious ratio with no or approximate knowledge of traffic demands. This research has investigated the quality of oblivious routing with respect to path dispersion, which is concerned with the number of paths; and path variation, which is concerned with how far the paths are from the shortest paths and the variation of path lengths. The results show the dispersion and the variation are high. A penalty method has been developed to improve the quality of oblivious routing. The penalty method strikes a good balance between the conflicting objectives of minimizing the oblivious ratio and optimizing the quality of the oblivious routing. This chapter is based on my published work [36].

3.1 Quality of routing

In designing a routing, there is usually a single objective to optimize, such as the link utilization in [8] or the network revenue in [45]. Besides a major objective, like link utilization, there are other factors to consider, such as path dispersion and path variation. These two factors are called the *quality of routing.*

Path dispersion is concerned with how many paths exist between each OD pair as specified by the routing. Path variation is concerned with how much the paths between each OD pair differ from the shortest path of the OD pair and how much they differ from each other. It is non-trivial to manage a routing with large path dispersion and large path variation. The algorithm to allocate paths to flows may become complex when there are many paths and the path variation is high. It is desirable that packets from different flows experience similar end-to-end delay. With large path variation, it may be difficult to achieve such fairness among flows. Long paths are usually not preferred. The delay jitter may be high if a flow takes multiple paths with high variation in lengths. Path dispersion and path variation are represented by two metrics: *number of paths* and *path length difference.* The number of paths between each OD pair of the routing computed by the LP is counted. For each OD pair, the path length difference is calculated as the difference between the length of the shortest path (calculated by Dijkstra's algorithm [15]) and the average of the lengths of all paths for the OD pair calculated by the LP. With a small length difference to the shortest paths, small variations between the path lengths are expected.

In the routing example as shown in Figure 3.1 (a), which reproduces Figure 2.1, there are two paths for $i_1 \rightarrow j_1$, i_1ABDj_1 and i_1ACDj_1. There is only one path for $i_1 \rightarrow j_1$ in Figure 3.1 (b), i_1ABDj_1. Similarly, OD pair $i_2 \rightarrow j_2$ has two paths in Figure 3.1 (a), while there is only one path in Figure 3.1 (b). The routing in Figure 3.1 (a) has higher path dispersion than the routing in Figure 3.1 (b) for each OD pair. The path(s) for each OD pair has the same length as the shortest path. Thus the two routings for each OD pair are the same with respect to the path variation. Therefore, the routing in Figure 3.1 (b) has better overall quality of routing than the routing in Figure 3.1 (a).



(a)

(b)

Figure 3.1: An Example: two routings for the topology in Figure 2.1

Applegate and Cohen [8] mention that it is desirable to consider the number of paths, i.e., path dispersion. Path dispersion was studied in [48] where the objective is a convex function and the traffic demands are known; while in [8] and this study, the objective is linear and the traffic demands are unknown.

3.2 Oblivious Routing

Based on [53], [10], Applegate and Cohen develop LP models to solve the oblivious routing problem in polynomial time in the context of the Internet. The following LP can compute the oblivious ratio of a network with $O(n^2m)$ variables and $O(nm^2)$ constraints [8], where m and n are the numbers of edges and nodes in the network respectively. Recall, the capacity of link l is denoted as $c(l)$. In the following, an edge is directed and a link is undirected. $f_{ij}(l) = \sum_{e:\text{link-of}(e)=l} f_{ij}(e)$, where l is a link, link-of(e) is the link corresponding to edge e. After applying LP duality theory, the variables $d_{ij}(e)$ disappear and new variables $\pi(l,m)$ and $p_l(i,j)$ are introduced. The authors also develop another LP for the case when approximate knowledge of TMs is available, as will be discussed in Section 4.3.5.

$$
\begin{array}{l}
\min_{r,f,\pi,p} r \\
f_{ij}(e) \text{ is a routing} \\
\forall \text{ links } l: \sum_m c(m)\pi(l,m) \leq r \\
\forall \text{ links } l, \forall \text{ pairs } i \to j: \\
\quad p_l(i,j) \geq f_{ij}(l)/c(l) \\
\forall \text{ links } l, \forall \text{ nodes } i, \forall \text{ edges } e = j \to k: \\
\quad \pi(l, \text{link-of}(e)) + p_l(i,j) - p_l(i,k) \geq 0 \\
\forall \text{links } l, m: \pi(l,m) \geq 0 \\
\forall \text{links } l, \forall \text{nodes } i: p_l(i,i) = 0 \\
\forall \text{links } l, \forall \text{nodes } i,j: p_l(i,j) \geq 0
\end{array}
\tag{3.1}
$$

The objective of LP (3.1) is to minimize the oblivious ratio. The routing calculated by LP (3.1) achieves low oblivious ratios with no knowledge of traffic demands [8]. However, the quality of routing including *path dispersion* and *path variation* is not considered.

It would be desirable to restrict the number of paths and/or the length difference of paths. To explicitly model these restrictions seems to be non-trivial: the LP model may become a mixed integer linear programming problem [4], which in general is hard to solve. Preliminary investigation of modeling this problem as a mixed integer programming problem reveals that, even on a small random network (10 nodes), the problem is hard to solve. In the next section, a penalty method is presented to construct a polynomial LP for this interesting yet challenging issue.

3.3 Balancing Oblivious Ratio and Quality of Routing: A Penalty Method

A penalty method is developed to balance the oblivious ratio and the quality of the oblivious routing. This problem can still be modeled as an LP: instead of solely minimizing the oblivious ratio r, a penalty component t is added to the objective function in LP (3.1). That is, the objective of LP (3.1) becomes $r + t$. Note, r in the objective is still the oblivious ratio as in LP (3.1). In deciding the penalty term, it is desirable to choose one that is tailored to the topology. As shown in the following, the penalty term is related to LP (3.1) (the LP without a penalty term) and the characteristics of the topology. As well, a penalty factor is used to make the scheme flexible. As shown in the experiments, the penalty factor can be tuned to balance the quality of the routing and the oblivious ratio. How to define the penalty term t is discussed now.

A small number of short paths is desirable. A natural way to achieve this is to penalize using paths composed of edges "far away" from the shortest path. This reference shortest path is computed using the link weights set inversely proportional to the link capacity, which is the heuristic approach by CISCO. Now define the distance of an edge to an OD pair, by calculating the distances of the two nodes on the edge to the shortest path of the OD pair. There may be several shortest paths. The one returned by Dijkstra's algorithm is chosen.

Denote $|(u,v)|_{hop}$ as the shortest distance between two nodes u and v with respect to hop count; $sp_{weight}(u,v)$ as the shortest path between two nodes u and v with respect to link weight. Node $n \in sp_{weight}(u,v)$ if n is on $sp_{weight}(u,v)$. Define the distance from node u to the OD pair $i \longrightarrow j$ as:

$$dist_u(i,j) = \min_{v:v \in sp_{weight}(i,j)} |(u,v)|_{hop}$$

That is, the distance from u to the OD pair $i \longrightarrow j$ is the minimum hop distance from u to any node on the shortest path with respect to weight for $i \longrightarrow j$.

The distance of an edge $u \longrightarrow v$ to an OD pair $i \longrightarrow j$ is:

$$dist_{uv}(i,j) = \frac{1}{2}[dist_u(i,j) + dist_v(i,j)]$$

The penalty of using an edge $u \longrightarrow v$ for an OD pair $i \longrightarrow j$ is defined as $dist_{uv}(i,j)$:

$$penalty_{uv}(i,j) = dist_{uv}(i,j)$$

Hence, using an edge far away from the shortest path of an OD pair will receive a large penalty. The definition of the penalty term t to LP (3.1) follows:

$$t = \frac{\beta}{\alpha} \sum_{i,j} \sum_{e} f_{ij}(e) penalty_e(i,j)$$

where β is called the *penalty factor*, and α is the penalty incurred by the optimal oblivious routing for the given topology. The oblivious routing $f'_{ij}(e)$ is calculated using LP (3.1). Then,

$$\alpha = \sum_{i,j} \sum_{e} f'_{ij}(e) penalty_e(i,j).$$

Dividing $\sum_e f_{ij}(e) penalty_e(ij)$ by α, which can be regarded as the characterization of the topology, the penalty term t is tailored to the topology. As a consequence, it is easier to select the penalty factor β. As shown in experiments, a single β can achieve good performance across various topologies.

The definition of the penalty term t implies that to minimize the objective $r + t$ as well as the penalty t, edges close to the shortest path will be used. Consequently, the paths will be made shorter. At the same time, because the paths have been shortened, traffic is squeezed onto the paths. As a result, the penalty term also reduces the number of paths. This will be shown in experimental results.

The LP with the penalty component is called the "penalty LP":

$$\begin{array}{l} \min_{r,f,\pi,p} r+t \\ f_{ij}(e) \text{ is a routing} \\ t = \frac{\beta}{\alpha}\sum_{ij}\sum_{e} f_{ij}(e) penalty_e(i,j) \\ \text{Other constraints and variables in LP (3.1)} \end{array} \quad (3.2)$$

In LP (3.2), $\alpha = \sum_{ij}\sum_{e} f'_{ij}(e) penalty_e(i,j)$ is computed ahead of time, and $f'_{ij}(e)$ is a routing computed by LP (3.1). This LP still has $O(mn^2)$ variables and $O(nm^2)$ constraints like LP (3.1).

3.4 Experimental Results

Internet Service Provider (ISP) topologies are regarded as proprietary information. The Rocketfuel project [62] deployed new techniques to measure ISP topologies and made them publicly available. Experiments are conducted at the level of PoPs (Point of Presence). Table 3.1 shows, for the topologies from Rocketfuel, the Autonomous System (AS) name and number, as well as the number of PoPs and links. The OSPF weights on the links are also provided [42]. The capacities of links are assigned according to the CISCO heuristics as in [8], i.e., the link weight is inversely proportional to the link capacity. The tier-1 ISP topology in Nucci et al. [47] is also used, denoted as POP 12, with the scaled link capacity provided in [47]. Random topologies generated by GT-ITM [2] are also used. For random topologies, link capacities are uniformly chosen on [10, 100].

Topology	ID	PoPs #	links #
Telstra (Australia)	AS 1221	57	59
Ebone (Europe)	AS 1755	23	38
Exodus (Europe)	AS 3967	22	37
Abovenet (US)	AS 6461	22	42
Sprint (Europe)	POP 12	12	17

Table 3.1: Tier-1 Topologies used in performance study.

LP (3.2) is studied by varying the penalty factor β from 1 to 10 with step size 1. The performance is judged by the oblivious ratio and quality of routing. Since all OD pairs are considered, *average number of paths* and *average path length difference* are used to measure the quality of routing. The average number of paths is the total number of calculated paths divided by the total number of OD pairs. To calculate the average path length difference, first the difference between the length of the shortest path and the average of the lengths of all the paths computed by the LP for each OD pair is calculated. Then the length differences are summed up and divided by the total number of OD pairs.

The results for ISP topologies are shown in Figure 3.2. Note that $\beta = 0$ in the figures is a special case: it is for the result calculated by LP (3.1) without the penalty component.

LP (3.1) yields the lowest oblivious ratio a network can obtain. However, LP (3.1) does not give a good quality routing: the average number of paths and average path length difference are high.

Figure 3.2 shows that as the penalty factor β increases, both the average number of paths and the average path length difference decrease. At the same time, the oblivious ratio increases. The results are expected, since LP (3.2) actually minimizes $r + \frac{\beta}{\alpha}\sum_{ij}\sum_{e}\{f_{ij}(e)penalty_e(ij)\}$, thus a larger β puts a greater penalty on using edges farther away from the shortest path. The experimental results show that the average number of paths and average path length difference decrease rapidly and level off; while the oblivious ratio increases only gradually.

Experiments are also conducted on random topologies. Figure 3.3 shows that the similarly excellent performance is achieved on the studied random topologies.

The experimental results show that it is possible to choose a proper β to balance the oblivious ratio and average number of paths and average path length difference. For example, a penalty factor of 1 or 2 gives good performance with respect to both the oblivious ratio and the quality of routing. Considering the dramatic improvement in the quality of routing, with only slight increase in oblivious ratio, this technique is very effective.

3.5 Conclusions

This research has investigated the quality of oblivious routing with respect to path dispersion and path variation. A penalty method has been developed to improve the quality of oblivious routing. The penalty method strikes a good balance between the conflicting objectives of minimizing the oblivious ratio and optimizing the quality of oblivious routing, as shown in the experiments for both realistic ISP topologies and random topologies.

The penalty method in this chapter handles the case in which no knowledge of traffic demands is available. It is extended in the next chapter to deal with approximation knowledge of traffic demands. It is one of the multipath selection methods in Section 4.3.5.

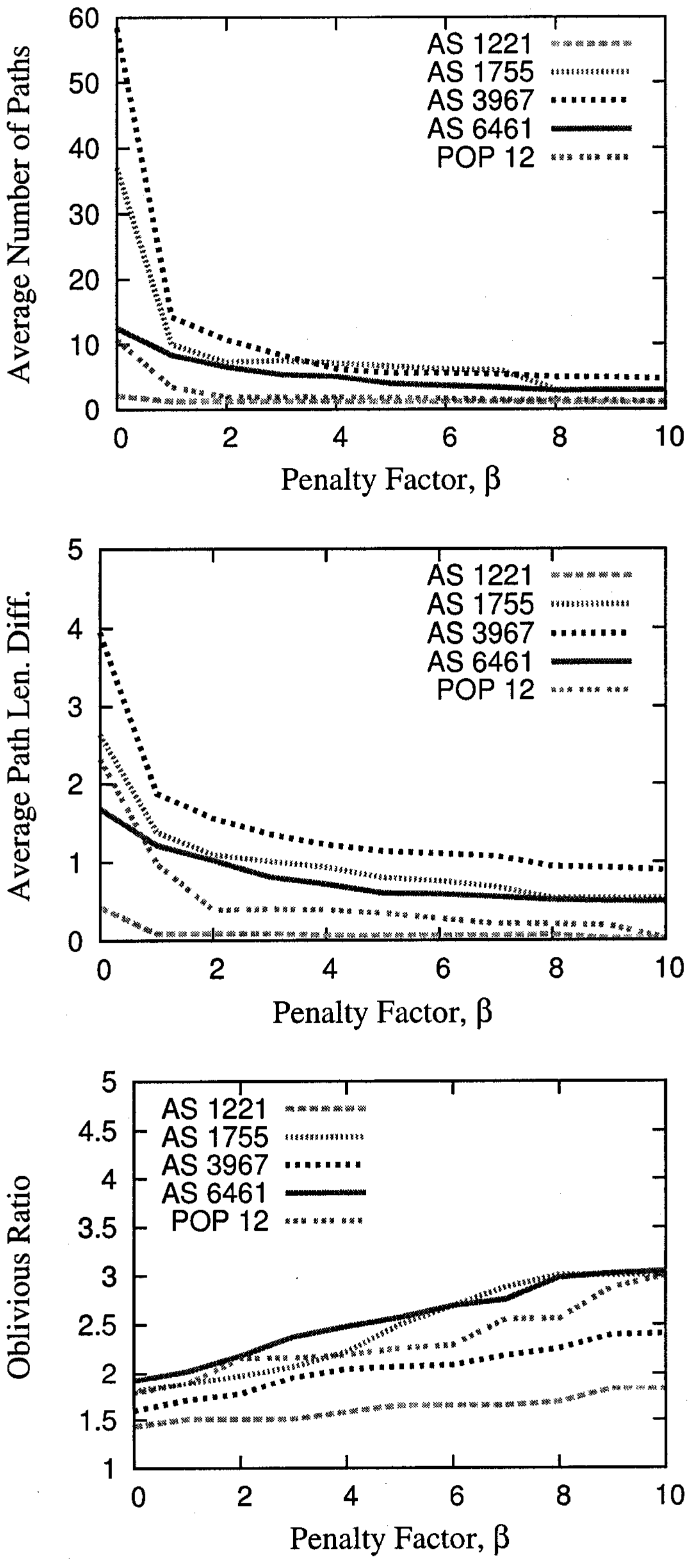


Figure 3.2: Experimental results for the penalty method on realistic ISP topologies

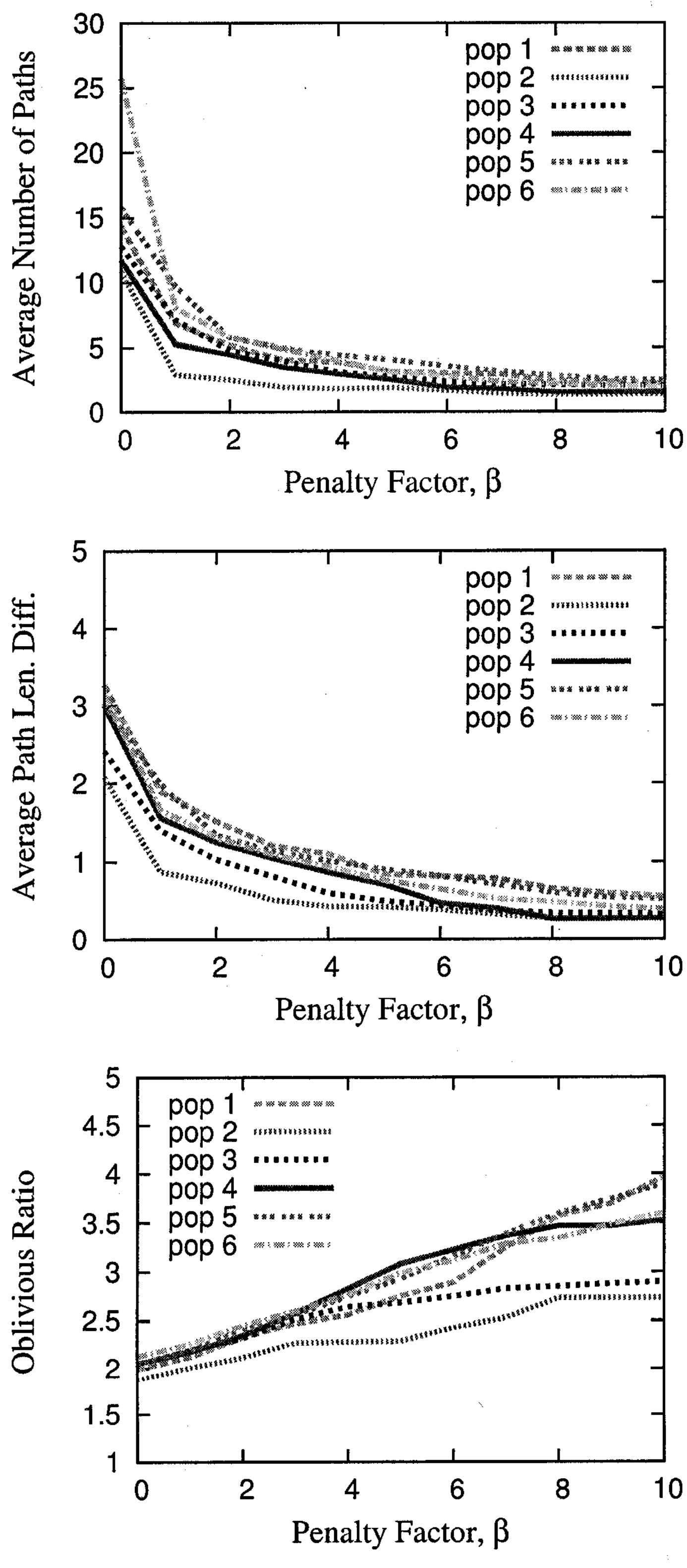


Figure 3.3: Experimental results for the penalty method on random topologies

Chapter 4

Multipath Oblivious Routing for Traffic Engineering

4.1 Introduction

Intra-domain traffic engineering is essential for the operation of an Internet Service Provider (ISP).[1] It is desirable to design a routing protocol that can balance network utilization, mitigate the impact of failures and attacks, and thus provide good quality of service to network users, with economical use of network resources. However, it is challenging to design such a routing protocol due to traffic changes and uncertainty. Network traffic is inherently changing and uncertain, due to factors such as the diurnal pattern, dynamic inter-domain routing, link failures, and attacks. Adaptive traffic resulting from overlay routing or multihoming [5, 22, 52] further aggravates the problems.[2]

There are three classes of solutions: link weight optimization [19, 20, 67, 68], traffic-adaptive approaches [16, 27, 58] and demand-oblivious routing [7, 8, 63]. Link weight optimization attempts to search for a set of link weights to optimize network performance, while how to find critical traffic matrices is investigated in [69]. It guarantees performance only for a limited set of traffic demands. An adaptive approach is responsive to traffic changes, so that the issues of stability and convergence [29] have to be addressed both in theory and in practice. Demand-oblivious routing is particularly promising; it promises an excellent performance guarantee with changing and uncertain traffic demands. Its performance is particularly good with approximate knowledge of traffic demands, which is made available by the recent great progress in traffic estimation, e.g. [13, 18, 32, 43, 61, 70, 71]. Moreover, oblivious routing provides a distributed solution, after the routing is computed centrally. In [63], the performance of oblivious routing is optimized for expected scenarios

[1]Intra-domain is about issues within a domain, usually an ISP network. Inter-domain is about issues between/among domains, where different domains may employ different policies for traffic engineering.

[2]An overlay network can be regarded as a virtual network on top of the physical network, with each virtual link consisting of one or more physical links. In multihoming, a customer or an ISP network has access to more than one external link to a single ISP or multiple ISPs [5].

and is guaranteed for unexpected scenarios.

However, it is non-trivial to implement oblivious routing as defined in [8]. A straightforward implementation is for each node to forward incoming packets according to the routing fractions computed by [8]. However, without careful attention, such a distributed implementation may lead to loops. Furthermore, an oblivious routing may involve a large number of paths between each origin-destination (OD) pair, which requires a large number of labels in an MPLS deployment [55]. It is thus desirable to route traffic on a small number of paths. However, since there are combinatorially many paths between each OD pair, it may be difficult to select a small set of paths that gives good performance.[3]

The challenges to implement oblivious routing are shared by many other optimization-based routing strategies. Recent progress along this line of research, including those being linear [4, 45], convex [48] or with game-theoretic concerns [6], has greatly advanced the state-of-the-art of routing. However, to achieve the optimal solution, such optimization-based approaches typically use an arc-formulation (see Section 4.3.2) as in oblivious routing [8]. Thus they may encounter the implementation issues as discussed above.

An efficient and deployable implementation of oblivious routing is investigated in this chapter. MORE, Multipath Oblivious Routing for traffic Engineering, is designed to obtain a close approximation to [8]. MORE can achieve an excellent performance guarantee when combined with approximate knowledge of traffic demands. However, it does not need frequent collection of network information like an adaptive approach. An oblivious routing guarantees the performance for much broader traffic demands than those specified by the traffic knowledge, since its performance is invariant with the scaling of traffic demands, thus temporary traffic spikes may be covered.

MORE can be static on an hourly, multi-hourly or even daily basis. Thus, MORE is much less concerned with stability and convergence issues [29] than an adaptive approach, which is responsive on a small time-scale, like seconds. MORE is a quasi-static routing, which is in contrast to an adaptive routing. It is static on a larger time scale, e.g., an hour or several hours, than an adaptive routing. A quasi-static routing changes much less frequently than an adaptive routing. MORE does not need changes to core routers, thus it can be efficiently implemented and gradually deployed. However, an adaptive approach, like TeXCP [27], needs to collect network information, which usually involves feedback from core routers.

This is the first investigation of a feasible implementation of demand-oblivious routing [8]. Extensive numerical and simulation studies demonstrate the excellent performance of MORE under varying TMs, link failures and an adversary attack. The door is thus opened for a

[3]In Chapter 3, an initial study has been done to balance the oblivious ratio and the quality of routing, which includes the metric for the number of paths, for the oblivious routing in [8] with no knowledge of traffic demands. Section 4.3.5 presents an extension of the method in Chapter 3, so that it can deal with the case where approximate knowledge of traffic demands is available.

viable deployment of oblivious routing, making it possible to provide ISPs an intra-domain traffic engineering technique robust to changing and uncertain environments. MORE is a promising option for traffic engineering, along with link weight optimization [19, 20, 67, 68] and adaptive approaches, like MATE [16], TeXCP [27] and [58].

The design of multipath oblivious routing is presented in Section 4.3, and its performance is evaluated in Section 4.4. After the discussions of implementation and deployment issues in Section 4.5, conclusions are drawn. This chapter is based on a technical report [34].

4.2 Related work

For OSPF/IS-IS, Fortz and Thorup [19, 20] deploy a local search technique to find a set of link weights for shortest path computation, which gives good performance for a given TM or a set of TMs. This is compatible with OSPF/IS-IS. However, it may not guarantee good performance for some traffic demands. Zhang et al. [67, 68] investigate routing optimization over multiple TMs and the tradeoff between average- and worst-case performance. Oblivious routing optimizes a worst case performance metric. However, the empirical study will show that MORE achieves a performance close to the optimal.

Recently, Kandula et al. [27] propose TeXCP, an adaptive routing on multiple paths. TeXCP uses feedback from core routers to discover path utilization. It then moves traffic from high-utilized paths to low-utilized path adaptively to achieve load balance throughout the network. Gallager's work [21] is a classic in adaptive routing. Shaikh et al. [58] and MATE [16] are also adaptive approaches. An adaptive approach has to address the issues of stability and convergence [29]. MORE, as a quasi-static solution, operates in a static way on a larger time-scale than an adaptive routing, thus the issues of stability and convergence are much less severe than for adaptive approaches.

Traffic estimation has made great progress, e.g. Feldmann et al. [18], Medina et al. [43], Bhattacharyya et al. [13], Zhang et al. [70, 71], Lakhina et al. [32] and Soule et al. [61]. See Soule et al. [61] for a recent survey. The network community begins to enjoy deeper understanding of the traffic structure and more accurate traffic estimation. Various models are proposed to study the spatial and temporal structure of the traffic. Techniques for fairly accurate traffic estimation are available, e.g., the Gravity model [70], so that traffic engineering techniques can take advantage of more accurate knowledge of traffic demands.

4.3 MORE: Multipath Oblivious Routing for Traffic Engineering

4.3.1 Overview

As discussed in Section 4.1, there are obstacles to the implementation of oblivious routing in [8], namely, potential routing loops and a prohibitive number of MPLS labels. A deployable oblivious routing, MORE, Multipath Oblivious Routing for traffic Engineering, is studied in the following.

A quasi-static routing is used, so that the fractions of traffic on the multiple paths between an OD pair do not change over a larger time period than an adaptive routing. The routing fractions may have to change, e.g., after severe network failures have happened. Such an implementation has the nice feature that issues like stability and convergence are much less severe than for adaptive approaches. As well, MORE alleviates the reliance on global network information: it can achieve excellent performance with a large time-scale traffic estimation, but it does not need to collect the instantaneous link load.

The key idea in MORE is to reformulate the oblivious routing in [8] on K paths to obtain LP (4.14), so that routing fractions are assigned to a set of predetermined paths between each OD pair.

Figure 4.1 gives an illustration of MORE. There is an OD pair $i \rightarrow j$ and a cloud of routers. For the OD pair $i \rightarrow j$, there are three paths, with routing fractions 0.5, 0.2 and 0.3, computed by LP (4.13) or LP (4.14). The incoming traffic will be forwarded on the three paths according to their routing fractions, i.e., 50%, 20% and 30% respectively. The amount of the traffic may change, however, the routing is oblivious to the change of the traffic, i.e., the routing fractions do not change. The traffic splitter splits incoming traffic according to the routing fractions. A concrete implementation of the traffic splitter is discussed in Section 4.4.5 for the simulation study.

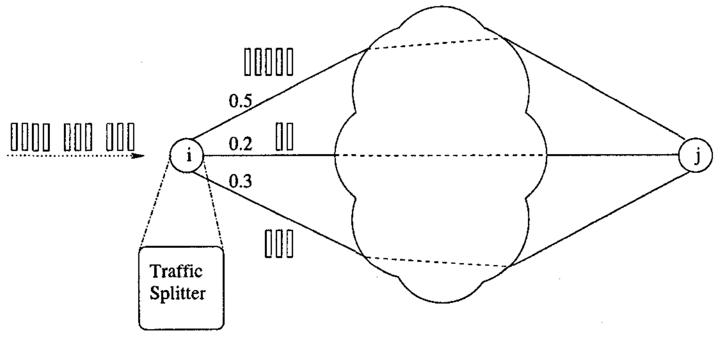


Figure 4.1: Illustration of MORE

4.3.2 Arc-Routing

An *arc-routing* $f_{ij}(e)$ specifies the fraction of traffic demand d_{ij} on edge e. For arc-routing, see Chapter 2 for the definitions of routing (Section 2.2), maximum link utilization (MLU) and optimal routing (Section 2.3) and the discussion of the competitive analysis framework (Section 2.3). For convenience, the definition of MLU and an optimal routing for an arc-routing are repeated here:

$$\mathrm{MLU}_{\mathrm{arc}}(\mathbf{tm}, \mathbf{f}) = \max_{e \in E} \sum_{i,j} d_{ij} f_{ij}(e)/c(e) \tag{4.1}$$

Given a TM $\mathbf{tm}$, an *optimal arc-routing* minimizes MLU:

$$\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = \min_{f} \max_{e \in E} \sum_{i,j} d_{ij} f_{ij}(e)/c(e) \tag{4.2}$$

4.3.3 Multipath routing

For each OD pair $i \to j$, up to K_{ij} paths are selected. For notational brevity, there are K paths for each OD pair. Path selection methods are discussed in Section 4.3.5. The set of paths for OD pair $i \to j$ is denoted as $P_{ij} = \{P_{ij}^1, ..., P_{ij}^K\}$. A multipath routing specifies, for each OD pair $i \to j$, a routing fraction vector on the set of paths for OD pair $i \to j$, defined as

$$< f_{ij}^1, ..., f_{ij}^K >, \sum_{k=1}^{K} f_{ij}^k = 1, f_{ij}^k \geq 0 \tag{4.3}$$

A *path-routing* f_{ij}^k specifies the fraction of traffic demand d_{ij} on path P_{ij}^k.

The MLU for a given path-routing $\mathbf{f}$ and a given traffic demand $\mathbf{tm}$ is:

$$\mathrm{MLU}_{\mathrm{path}}(\mathbf{tm}, \mathbf{f}) = \max_{l \in E} \sum_{ij} d_{ij} \sum_{k} \delta_{ij}^k(l) f_{ij}^k / c(l) \tag{4.4}$$

Here $\delta_{ij}^k(l)$ is an indicator function, which is 1 if $l \in P_{ij}^k$, 0 otherwise, where $l \in P_{ij}^k$ is used to denote edge l is on path P_{ij}^k.

Given $\mathbf{tm}$, an *optimal path-routing* minimizes the MLU:

$$\mathrm{OPTU}_{\mathrm{path}}(\mathbf{tm}) = \min_{\mathrm{f}:\mathbf{f} \text{ is a path-routing}} \mathrm{MLU}_{\mathrm{path}}(\mathbf{tm}, \mathbf{f}) \tag{4.5}$$

For a given routing $\mathbf{f}$ and a given traffic matrix $\mathbf{tm}$, the *performance ratio* is,

$$\mathrm{PERF}(\mathbf{f}, \{\mathbf{tm}\}) = \frac{\mathrm{MLU}(\mathbf{tm}, \mathbf{f})}{\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm})} \tag{4.6}$$

This applies to both an arc- and a path-routing, thus there is no subscript to MLU. Similar to arc-routing, the optimal oblivious ratio and optimal oblivious routing (Section 2.4.2) for path-routing can be defined.

4.3.4 LP Formulation for MORE

In this section, LP models for multipath oblivious routing are derived. The arc formulation in Applegate and Cohen [8] is replaced with a path formulation to compute an optimal oblivious routing and its ratio. In an arc formulation, routing variables are on links and flow conservation constraints are at each node for each OD pair. In a path formulation, routing variables are on paths and flow conservation constraints are implicitly satisfied on each path. The case with approximate knowledge of traffic demands is discussed first.

Similar to Applegate and Cohen [8], the optimal oblivious routing can be obtained by solving an LP with a polynomial number of variables, but infinitely many constraints. With the approximate knowledge that d_{ij} is in the range of $[a_{ij}, b_{ij}]$, we have the "master LP":

$$\begin{array}{l} \min_{r,f,d} r \\ \mathbf{f} \text{ is a path-routing} \\ \forall \text{ edges } l, \forall \alpha > 0, \forall \text{ TMs } \mathbf{tm} \text{ with } \mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = \alpha, \text{ and } a_{ij} \leq d_{ij} \leq b_{ij} : \\ \quad \sum_{ij} d_{ij} \sum_{k} \delta_{ij}^{k}(l) f_{ij}^{k} / c(l) \leq \alpha r \end{array} \tag{4.7}$$

The oblivious ratio is invariant with the scaling of the traffic matrices or the scaling of the edge capacity. Thus, when computing the oblivious ratio, it is sufficient to consider traffic matrices with $\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = 1$. Another benefit of using traffic matrices with $\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = 1$ is that the objective of the LP, the oblivious ratio r, is equal to the MLU of the oblivious routing.

Since the oblivious ratio r is invariant with respect to the scaling of TMs, we can consider a scaled TM $\mathbf{tm}' = \lambda \cdot \mathbf{tm}$. With $\lambda = 1/\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm})$, we have $\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}') = 1$. Under these conditions, the master LP (4.7) becomes:

$$\begin{array}{l} \min_{r,f,d} r \\ \mathbf{f} \text{ is a path-routing} \\ \forall \text{ edges } l : \\ \quad \forall \text{ TMs } \mathbf{tm} \text{ with } \mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = 1, \lambda > 0, \text{ and } \lambda a_{ij} \leq d_{ij} \leq \lambda b_{ij} : \\ \quad \sum_{ij} d_{ij} \sum_{k} \delta_{ij}^{k}(l) f_{ij}^{k} / c(l) \leq r \end{array} \tag{4.8}$$

Given a path-routing $\mathbf{f}$, the constraints of the master LP (4.8) can be checked by solving the following "slave LP" for each edge l to examine if the objective is upper bounded by r.

For the condition "$\forall$ TMs $\mathbf{tm}$ with $\mathrm{OPTU}_{\mathrm{arc}}(\mathbf{tm}) = 1$", the flow definition on edges, as in (2.5), is needed. LP formulations can be simplified by collapsing flows g_{ij} on an edge e with the same origin by $g_i(e) = \sum_j g_{ij}(e)$. With $g_i(e) = \sum_j g_{ij}(e)$, the constraints "$\forall$ pairs $i \to j : \sum_{e \in out(j)} g_i(e) - \sum_{e \in in(j)} g_i(e) + d_{ij} = 0$" are equivalent to the two sets of constraints in (2.5), "$\forall$ pairs $i \to j : \sum_{e \in in(j)} g_{ij}(e) - \sum_{e \in out(j)} g_{ij}(e) = d_{ij}$" and "$\forall$ pairs $i \to j, k \neq i, j : \sum_{e \in out(k)} g_{ij}(e) - \sum_{e \in in(k)} g_{ij}(e) = 0$". The flow conservation constraint, $\forall$ pairs $i \to j : \sum_{e \in out(j)} g_i(e) - \sum_{e \in in(j)} g_i(e) + d_{ij} = 0$, is relaxed from equality to ≤ 0 in (4.9), which allows for OD pair $i \to j$ to deliver more flow than demanded, and does not affect the MLU of 1.

The condition "$\forall$ TMs **tm** with $\text{OPTU}_{\text{arc}}(\mathbf{tm}) = 1$" in (4.8) is equivalent to the constraints "$\forall$ pairs $i \to j : \sum_{e \in out(j)} g_i(e) - \sum_{e \in in(j)} g_i(e) + d_{ij} \leq 0$" and "$\forall$ edges e : $\sum_i g_i(e) \leq c(e)$" in (4.9). Therefore, the constraints in (4.9) are equivalent with the conditions of "$\forall$ TMs **tm** with $\text{OPTU}_{\text{arc}}(\mathbf{tm}) = 1, \lambda > 0$, and $\lambda a_{ij} \leq d_{ij} \leq \lambda b_{ij}$" in (4.8). Routing f_{ij}^k are constant in (4.9), and flow $g_{ij}(e)$, demand d_{ij} and λ are variables.

$$\begin{array}{ll}
\max\limits_{g,d,\lambda} \sum\limits_{ij} d_{ij} \sum\limits_{k} \delta_{ij}^k(l) f_{ij}^k / c(l) & \\
\forall \text{ pairs } i \to j : \sum\limits_{e \in out(j)} g_i(e) - \sum\limits_{e \in in(j)} g_i(e) + d_{ij} \leq 0 & \Leftarrow w_l(i,j) \\
\forall \text{ edges } e : \sum\limits_{i} g_i(e) \leq c(e) & \Leftarrow \pi_l(e) \\
\forall \text{ pairs } i \to j : d_{ij} - \lambda b_{ij} \leq 0 & \Leftarrow \kappa_l^+(i,j) \\
\forall \text{ pairs } i \to j : -d_{ij} + \lambda a_{ij} \leq 0 & \Leftarrow \kappa_l^-(i,j) \\
\forall \text{ pairs } i \to j, \text{ edges } e : d_{ij} \geq 0, g_i(e) \geq 0 & \\
\lambda > 0 &
\end{array} \tag{4.9}$$

The dual of LP (4.9) is LP (4.10). To help make the derivation of the dual LP (4.10) clearer, leftarrows ($\Leftarrow$) are used to indicate correspondence between dual variables and primal constraints in LP (4.9). In dual LP (4.10), leftarrows are used to indicate correspondence between primal variables and dual constraints.

$$\begin{array}{ll}
\min\limits_{\pi,w,\kappa^+,\kappa^-} \sum\limits_{e} c(e)\pi_l(e) & \\
\forall \text{ pairs } i \to j : w_l(i,j) + \kappa_l^+(i,j) - \kappa_l^-(i,j) \geq \sum\limits_{k} \delta_{ij}^k(l) f_{ij}^k / c(l) & \Leftarrow d_{ij} \\
\forall \text{ nodes } i, \forall \text{ edges } (u,v) : \pi_l(u,v) + w_l(i,u) - w_l(i,v) \geq 0 & \Leftarrow g_i(u,v) \\
\sum\limits_{i,j} \{a_{ij}\kappa_l^-(i,j) - b_{ij}\kappa_l^+(i,j)\} \geq 0 & \Leftarrow \lambda \\
\forall \text{ edges } e : \pi_l(e) \geq 0 & \\
\forall \text{ pairs } i \to j : w_l(i,j) \geq 0, \kappa_l^+(i,j) \geq 0, \kappa_l^-(i,j) \geq 0 & \\
\forall \text{ nodes } i : w_l(i,i) = 0, \kappa_l^+(i,i) = 0, \kappa_l^-(i,i) = 0 &
\end{array} \tag{4.10}$$

According to LP duality theory [4], the primal LP and its dual LP have the same optimal value if they exist. Thus, LP (4.9) and LP (4.10) are equivalent. Consequently, LP (4.11) and LP (4.12) are equivalent. For computing the optimal oblivious ratio, the master LP (4.8) can be reformulated as either LP (4.11) or LP (4.12).

$$\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a path-routing} \\
\forall \text{ edges } l : \\
\quad \text{objective of LP (4.9)} \leq r
\end{array} \tag{4.11}$$

$$\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a path-routing} \\
\forall \text{ edges } l : \\
\quad \text{objective of LP (4.10)} \leq r
\end{array} \tag{4.12}$$

Because LP (4.10) is a minimization problem, its objective can be used in place of the objective of LP (4.9) in the "$\leq r$" constraints of LP (4.8). Replacing the constraint in the master LP (4.8) with LP (4.10), LP (4.13) is obtained to compute the oblivious ratio using K paths. It is polynomial in the numbers of nodes, edges and selected paths.

$$
\begin{array}{l}
\min_{r,f,\pi,w,\kappa^+,\kappa^-} \quad r \\
\mathbf{f} \text{ is a path-routing} \\
\forall \text{ edges } l: \\
\quad \sum_e c(e)\pi_l(e) \le r \\
\quad \forall \text{ pairs } i \to j: w_l(i,j) + \kappa_l^+(i,j) - \kappa_l^-(i,j) \ge \sum_k \delta_{ij}^k(l) f_{ij}^k / c(l) \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \pi_l(u,v) + w_l(i,u) - w_l(i,v) \ge 0 \\
\quad \sum_{i,j} \{a_{ij}\kappa_l^-(i,j) - b_{ij}\kappa_l^+(i,j)\} \ge 0 \\
\quad \forall \text{ edges } e: \pi_l(e) \ge 0 \\
\quad \forall \text{ pairs } i \to j: w_l(i,j) \ge 0, \kappa_l^+(i,j) \ge 0, \kappa_l^-(i,j) \ge 0 \\
\quad \forall \text{ nodes } i: w_l(i,i) = 0, \kappa_l^+(i,i) = 0, \kappa_l^-(i,i) = 0
\end{array}
\tag{4.13}
$$

When there is no knowledge of the traffic demands, i.e., the range $[a_{ij}, b_{ij}]$ for d_{ij} becomes $[0, \infty)$, the LP to compute the oblivious routing is obtained by removing the variables $\kappa_l^+(i,j)$ and $\kappa_l^-(i,j)$, as in LP (4.14).

$$
\begin{array}{l}
\min_{r,f,\pi,w} \quad r \\
\mathbf{f} \text{ is a path-routing} \\
\forall \text{ edges } l: \\
\quad \sum_e c(e)\pi_l(e) \le r \\
\quad \forall \text{ pairs } i \to j: w_l(i,j) \ge \sum_k \delta_{ij}^k(l) f_{ij}^k / c(l) \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \pi_l(u,v) + w_l(i,u) - w_l(i,v) \ge 0 \\
\quad \forall \text{ edges } e: \pi_l(e) \ge 0 \\
\quad \forall \text{ pairs } i \to j: w_l(i,j) \ge 0 \\
\quad \forall \text{ nodes } i: w_l(i,i) = 0
\end{array}
\tag{4.14}
$$

4.3.5 MultiPath Selection

Section 4.3.4 presents LP (4.13) and LP (4.14) for computing routing fractions on given multiple paths. This section discusses how to select multiple paths for each OD pair. The objective is to select multiple paths that give a low oblivious ratio. Three approaches, namely, sp$K$, mix$K$ and focus$K$, are investigated.

In sp$K$, K shortest paths with respect to hop count for each OD pair are selected.

In mix$K$, first K shortest paths with respect to hop count are found, as in sp$K$. These shortest paths serve as base paths. Then, the K paths are sorted in increasing order of their hop counts. After that, for each shortest path, its edge-disjoint paths are searched for and recorded, until K paths are found. Long paths are not desired, so that only disjoint paths that are not M hops longer than the base paths ($M = 3$) are searched for. The name "mix$K$" reflects that it is a mixture of shortest paths and their disjoint paths. K shortest paths are found first, in case none of them has an eligible disjoint path. In this case, the K shortest paths are chosen as the mix$K$ paths.

The method focus$K$ is based on the method in Chapter 3. In Chapter 3, a method is designed to implicitly reduce the number of paths and path lengths of the oblivious routing in Applegate and Cohen [8], with only negligible increase of the oblivious ratio. The basic idea is to put a penalty on using an edge far away from the shortest path for an OD pair. Thus, this method essentially focuses on short paths for each OD pair. Here, an extension is made to the method in Chapter 3 by considering range restrictions on traffic demands.

LP (4.15) is from Applegate and Cohen [8]. It computes the oblivious routing and its ratio of a topology, when knowledge of traffic demands is given in the range restriction format, i.e., $\forall$ pairs $i, j, 0 \le a_{ij} \le d_{ij} \le b_{ij}$. Compared with LP (3.1), LP (4.15) has more variables and more constraints to reflect the range restriction on traffic demands.

$$
\begin{array}{l}
\min\limits_{r,f,\pi,p,s^+,s^-} \quad r \\
f_{ij}(e) \text{ is an arc-routing} \\
\forall \text{ links } l : \sum_m c(m)\pi(l,m) \le r \\
\forall \text{ links } l, \forall \text{ pairs } i \to j : \\
\quad p_l(i,j) + s^+(i,j) - s^-(i,j) \ge f_{ij}(l)/c(l) \\
\forall \text{ links } l, \forall \text{ nodes } i, \forall \text{ edges } e = j \to k : \\
\quad \pi(l, \text{link-of}(e)) + p_l(i,j) - p_l(i,k) \ge 0 \\
\forall \text{ links } l : \sum_{ij} (b_{ij} s^+(i,j) - a_{ij} s^-(i,j)) \le 0 \\
\forall \text{links } l, m : \pi(l,m) \ge 0 \\
\forall \text{links } l, \forall \text{nodes } i : p_l(i,i) = 0 \\
\forall \text{links } l, \forall \text{nodes } i, j : p_l(i,j), s^+(i,j), s^-(i,j) \ge 0
\end{array}
\qquad (4.15)
$$

After computing the arc-routing $\mathbf{f}$ using LP (4.15), similar to Section 3, the following "penalty LP with range restriction" can be obtained:

$$
\begin{array}{l}
\min\limits_{r,f,\pi,p,s^+,s^-} \quad r + t \\
f_{ij}(e) \text{ is an arc-routing} \\
t = \frac{\beta}{\alpha} \sum_{ij} \sum_e f_{ij}(e) penalty_e(i,j) \\
\text{Other constraints and variables in LP (4.15)}
\end{array}
\qquad (4.16)
$$

In LP (4.16), $\alpha = \sum_{ij} \sum_e f'_{ij}(e) penalty_e(i,j)$ is computed ahead of time, and $f'_{ij}(e)$ is an arc-routing computed by LP (4.15). Here β is the penalty factor and $penalty_{uv}(i,j)$ measures the distance from edge (u,v) to OD pair $i \to j$. The larger β, the more pressure deterring use of an edge far away from the shortest path. The penalty $penalty_{uv}(i,j)$ is half the sum of the distances of nodes u and v to the shortest path of i to j. Similar to Chapter 3, when computing the shortest path of OD pair $i \to j$, the metric of link weight is used; when computing the shortest distance from a node to an OD pair $i \to j$, the metric of hop count is used.

After computing the oblivious routing using LP (4.16), K paths are extracted. In the performance study, up to 20 shortest paths are extracted from the resultant oblivious routing with routing fractions ≥ 0.001.

LP (4.15) and LP (4.16) can handle the case in which no knowledge of traffic demands is available, by removing the constraints about $a_{ij} \le d_{ij} \le b_{ij} \ge 0$, i.e., by removing variables $s^+(i,j)$ and $s^-(i,j)$. The LPs for the case in which no knowledge of traffic demands is available are shown in Section 3.2 and Section 3.3.

The path selection methods are complementary to the work using multipath routing, like TeXCP [27], an adaptive multipath routing. For example, rather than using K shortest path as the default method in TeXCP, it can use either mix$K$ or focus$K$, in a hope to achieve better performance. The path selection methods discussed here are not exhaustive - better designs are likely possible.

4.4 Performance Study

The performance of MORE is evaluated by numerical and simulation studies. Performance metrics are the oblivious ratio of a routing and the maximum link utilization (MLU) a routing incurs.

4.4.1 Data

Topology. Rocketfuel tier-1 ISP topologies [62, 42], AS 1755, AS 3967 and AS 6461, are used in the performance study. The tier-1 ISP topology in Nucci et al. [47], POP 12, is also used, with the scaled link capacity provided in [47]. See Table 3.1 for the numbers of PoPs and links of these topologies. Random topologies generated by GT-ITM [2] are also used.

Gravity TM. Similar to [8, 27], the Gravity model [70] is used to generate synthetic TMs. The Gravity model is developed in [70] as a fast and accurate estimation of traffic matrices, in which, the traffic demand between an OD pair is proportional to the product of the traffic flowing into/out of the origin/destination. A heuristic approach is used, similar to that in [8], in which the volume of traffic flowing into/out of a POP is proportional to the combined capacity of links connecting with the POP. Then a complete Gravity TM is extrapolated.

Lognormal TM. The log-normal model in Nucci et al. [47] is also used to generate synthetic TMs. In the first step, traffic entries are generated using a log-normal distribution. Then these entries are associated with OD pairs according to a heuristic approach similar to that recommended in [47]. That is, OD pairs are ordered by the first metric of their fan-out capacities. The fan-out capacity of a node is the sum of the capacities of links incident with it. The fan-out capacity of an OD pair is the minimum of the fan-out capacities of the two nodes. Ties are broken by the second metric of connectivity, defined as the number of links incident to a node. Similarly, the minimum is taken for the two nodes. The traffic entries are sorted and matched with the sorted OD pairs. Thus a TM is generated.

Similar to [8], in the experiments, when approximate knowledge is available, a *base TM* with the entry d_{ij} for OD pair $i \rightarrow j$, and an error margin $w > 1$ are considered, so that the traffic for $i \rightarrow j$ is in the range of $[d_{ij}/w, w * d_{ij}]$.

4.4.2 MultiPath selection

First, the performance of the path selection methods, namely, sp$K$, mix$K$ and focus$K$, is studied. The benchmark is the method in Applegate and Cohen [8], which can achieve the lowest oblivious ratio for a given topology. Hereafter, the method in Applegate and Cohen [8] is referred to as AC. It is non-trivial to implement the routing computed by AC as discussed in Section 4.1. Thus a close multipath approximation to AC is desirable.

The path selection methods are compared with the approach of link weight optimization [19] (referred to as WtOpt[4]) and the CISCO heuristic approach of setting link weight inversely proportional to the link capacity (referred to as InvCap). For MORE, after selecting paths, LP (4.13) or LP (4.14) is used to compute the optimal multipath oblivious routing. Use sp$K$, mix$K$ and focus$K$ to refer to the resultant routing. WtOpt and InvCap are methods to set link weights, with which, a shortest path algorithm can determine a routing. Multiple paths with equally least weight may be possible for WtOpt and InvCap and traffic is equally split over these paths. WtOpt and InvCap also refer to the routings computed by the link weights they find respectively. For WtOpt, link weights are set by searching for 5 synthetic Lognormal TMs [47] which have optimal MLU=0.3. Link weights have also been set by searching for a Gravity TM for WtOpt. The results are not as good as those shown here.

Table 4.1 presents the oblivious ratios for various path selection methods, as well as the ratios for WtOpt and the ratios computed by AC, when there is no knowledge of the traffic demands. As expected, there is a gap between the oblivious ratios computed by AC and those by the multipath approximation, namely, sp20, mix20 and focus20. With more paths, e.g., 50 paths, the gap can become narrower. However, a small number of paths may be desirable, thus results for 30 or 50 paths are not presented. For POP 12, multipath approximation methods sp20 and mix20 can achieve the same oblivious ratio as AC. The results also show that WtOpt [19] has large oblivious ratios. WtOpt can consider multiple TMs. However, it is non-trivial for WtOpt to optimize for all or a continuous set of TMs.[5] Applegate and Cohen [8] studied the performance of InvCap and showed its high oblivious ratios, e.g., 16.60 (AS 1755), 49.20 (AS 3967) and 233.98 (AS 6461).

Figure 4.2 shows the performance of the various path selection methods, sp$K$, mix$K$ and focus$K$, when approximate knowledge of the TM is available, with a Gravity base TM, compared with AC. For AS 1755, all path selection methods have good performance when the error margin is small, with sp20 jumping up when the error margin increases and mix20 maintaining the best performance. For AS 3967 and AS 6461, focus20 has

[4]Implementation of WtOpt is borrowed from Chun Zhang, A PhD student in the Department of Computer Science, the University of Massachusetts, Amherst.

[5]WtOpt and InvCap are compatible with OSPF, while MORE is generally not. Here we study which routing can achieve better performance w.r.t. oblivious ratio, without considering its forwarding scheme.

Topology	WtOpt	sp20	mix20	focus20	AC
AS 1755	27.840	3.306	2.718	1.950	1.781
AS 3967	17.613	3.442	5.061	3.428	1.623
AS 6461	28.889	4.250	4.250	2.107	1.910
POP 12	3.813	1.785	1.785	2.161	1.785

Table 4.1: Oblivious ratios for various routings methods: WtOpt [19], sp$K$, mix$K$, focus$K$ and AC [8], when no knowledge of traffic demands is available.

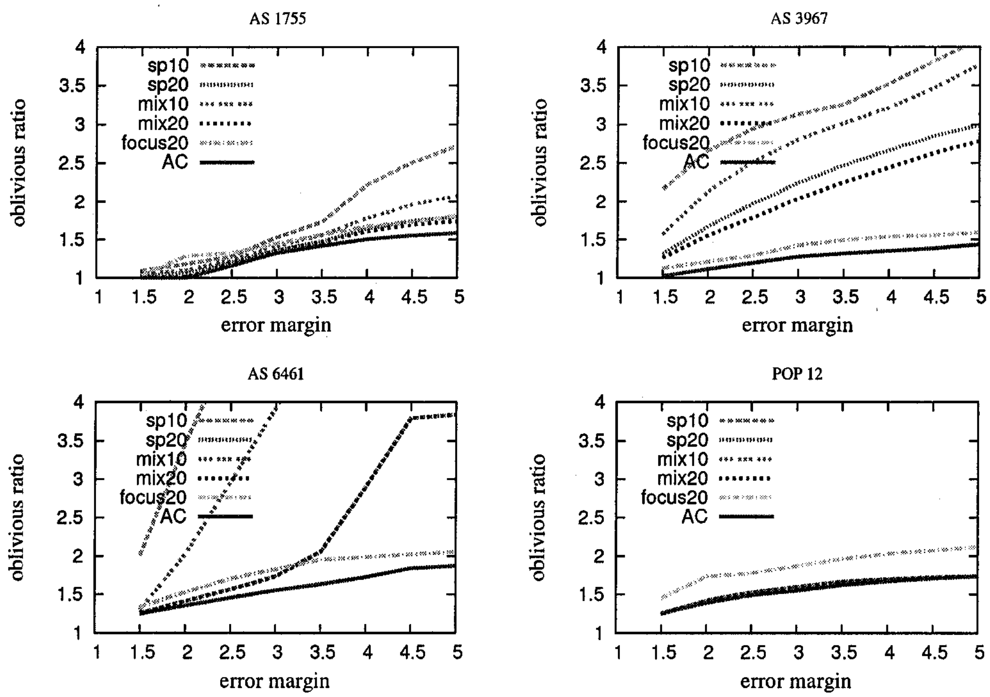


Figure 4.2: Oblivious ratio vs. error margin for various path selection methods

overall good performance. For POP12, sp$K$ and mix$K$, for $K = 10, 20$, have similar results, with performance very close to AC. As well, comparing with the results in Table 4.1, the performance of focus20 for AS 3967 and mix20 for AS 1755 are much better when there is approximate knowledge of traffic demands.

The performance of InvCap, WtOpt, focus20 and mix20 is also studied on 100 random TMs. When there is no knowledge of the TM, an entry in the traffic matrix is uniformly set on $[10, 100]$; when the error margin $w = 2.0$, first the base TM for d_{ij}'s is decided by the Gravity model, then 100 random TMs are uniformly generated on $[d_{ij}/w, d_{ij} * w]$. The MLU that a routing incurs is compared with the optimal, denoted as MLU/OPT. Figure 4.3 shows the average MLU/OPT and the 95% confidence interval of each routing method. The results show that MORE can achieve good performance. When there is no knowledge of the TM, focus20 has good performance for AS 1755, AS 3967 and AS 6461; while mix20 has good performance for POP 12. When the error margin $w = 2.0$, both focus20 and

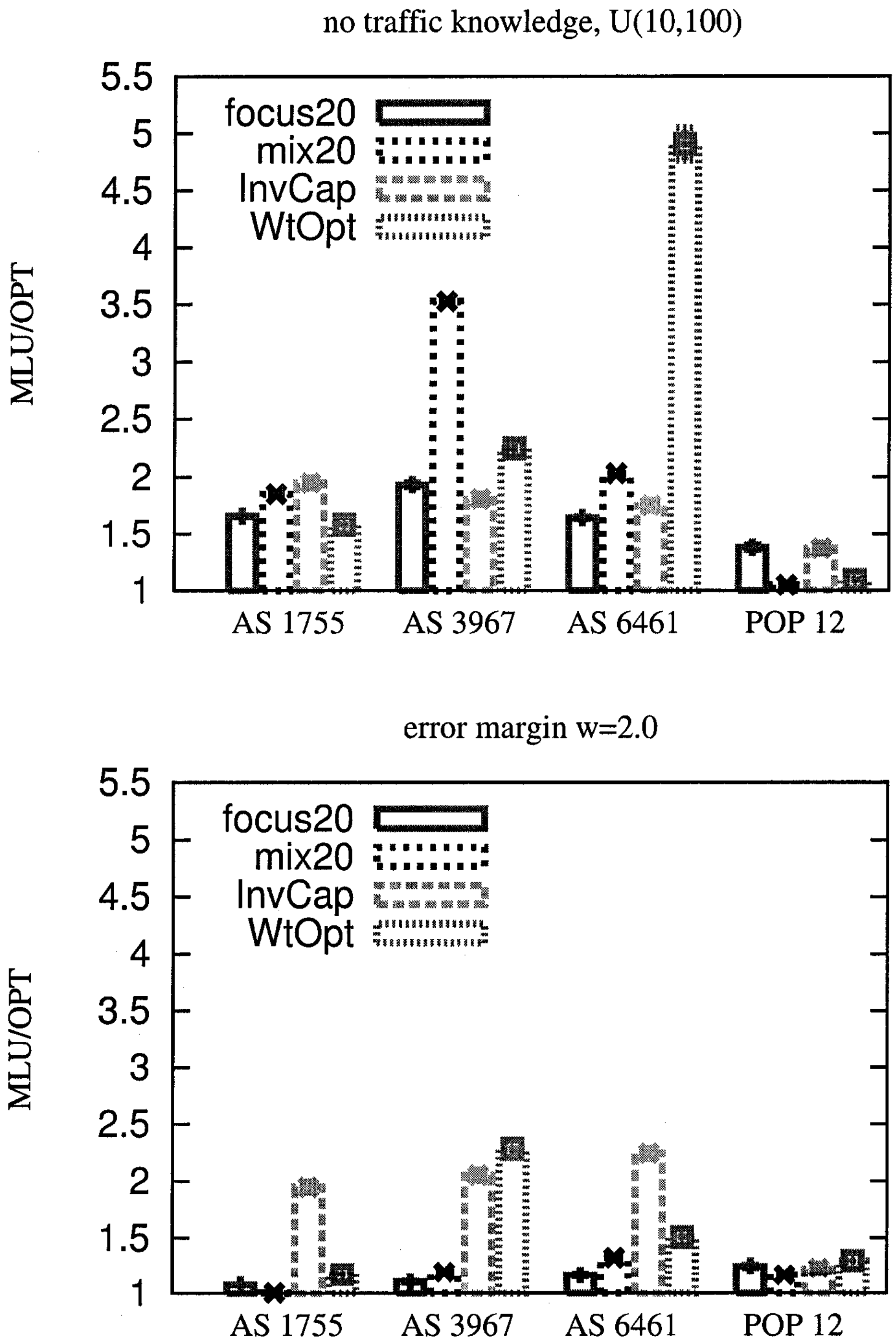


Figure 4.3: MLU/OPT of various routing methods: InvCap, WtOpt, focus20 and mix20. Average MLU/OPT and 95% confidence interval for 100 random TMs 1) without any knowledge of TM, uniformly chosen on [10,100] (top), and 2) with error margin 2.0 (bottom).

mix20 have low MLU/OPT. InvCap and WtOpt may have good performance in some cases, however, they may incur high MLU/OPT. InvCap does not have an explicit objective to optimize MLU for one or a set of TMs, thus it may not have good performance for some TMs.

For lack of ISP topologies, random topologies are also used to attempt to justify the performance of the path selection methods. One hundred random topologies with 25 PoPs are generated using GT-ITM [2]. Link capacities are uniformly chosen on [10, 100]. Figure 4.4 shows the performance of focus20 and mix20 on random topologies, compared with AC. The topologies are ordered in increasing order of their oblivious ratios using AC. We observe that on the studied random topologies, both focus20 and mix20 have good performance: they can achieve oblivious ratios close to that achieved by AC. Mix20 performs particularly well, tracking closely the curve of AC, especially in the case where there is approximate knowledge of traffic demands ($w = 2.0$).

A conclusive judgment on the performance of the proposed path selection methods cannot be made based on the study of a sample of ISP topologies and 100 random topologies. However, high confidence is gained that a multipath oblivious routing can have a close approximation to AC.

In MORE, paths can be chosen and an optimal oblivious routing can be computed before conducting further traffic engineering tasks. That is, the best path selection method (among the proposed methods) for a network can be chosen. In later studies, path selection methods are specified according to Table 4.2. When there is approximate knowledge of traffic demands, error margin $w = 2.0$ is used, which can be interpreted as a tolerance of 100% error in traffic estimation.[6] The current traffic estimation techniques can achieve an error much finer than 100%, e.g., Zhang et al. [70] and Soule et al. [61]. Table 4.2 also shows the oblivious ratios for $w = 2.0$ for the path selection methods.

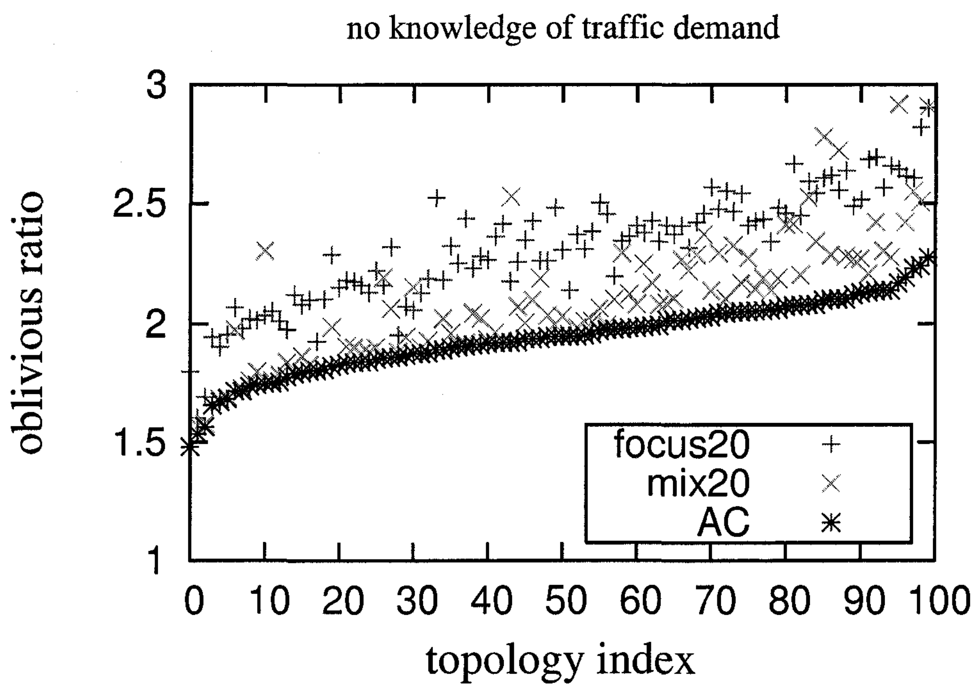
Topology	AS 1755	AS 3967	AS 6461	POP 12
Path selection	mix20	focus20	focus20	mix10
obliv. ratio ($w = 2.0$)	1.068	1.156	1.513	1.422

Table 4.2: Path selection methods in experiments

4.4.3 Link failure

Applegate et al. [7] study failure restoration for arc-based oblivious routing [8]. Failure restoration for MORE is studied in this section. A link in a POP level topology usually represents a set of physical links. Thus link failures of physical links may only cause link "degradation", rather than link failure for the POP level link. Similar to [7], link failure is

[6]An optimal oblivious routing for the range $[a_{ij}, b_{ij}]$ guarantees the performance not only for TMs in the range, but also those scaled TMs.



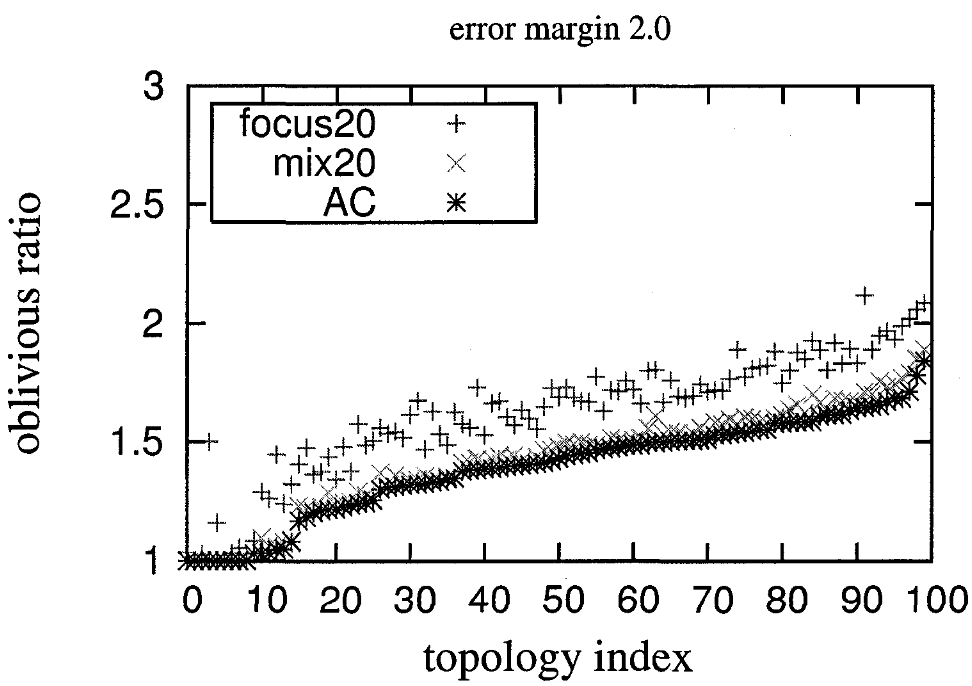


Figure 4.4: Performance of path selection methods on 100 random topologies, comparing with AC.

used to refer to the scenarios in which physical links fail, while a POP level link may still work.

Three restoration strategies, *nochange*, *reoptimization* and *augmentation*, are investigated. In nochange, the routing is kept unchanged (if the failure does not cause a POP level link failure, i.e., it does not cause a path to break). To evaluate this, LP (4.9) is used to compute the oblivious ratio. In another extreme, reoptimization, the multipath oblivious routing is reoptimized for the new topology after link failures occur, using LP (4.13) or LP (4.14). An approach in between, augmentation, is to reoptimize only for the affected OD pairs, which use the link(s) with failure. The LP derivation for augmentation is similar to that for LP (4.13) and LP (4.14), and the resultant LPs are similar, except that the routing variables for the unaffected OD pairs are constant. LP (4.17) is the LP formulation for augmentation with the approximate knowledge that d_{ij} is in the range of $[a_{ij}, b_{ij}]$. The case in which no knowledge is available can be dealt with similarly as for LP (4.14).

$$\begin{array}{l}
\min\limits_{r,f,\pi,w,\kappa^+,\kappa^-} \quad r \\
\mathbf{f} \text{ is a path-routing defined on affected OD pairs} \\
\forall \text{ edges } l: \\
\quad \sum\limits_{e} c(e)\pi_l(e) \leq r \\
\quad \forall \text{ pairs } i \to j : w_l(i,j) + \kappa_l^+(i,j) - \kappa_l^-(i,j) \geq \sum\limits_{k} \delta_{ij}^k(l) f_{ij}^k / c(l) \\
\qquad (f_{ij}^k \text{ is constant if OD pair } i \to j \text{ is not affected}) \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v) : \pi_l(u,v) + w_l(i,u) - w_l(i,v) \geq 0 \\
\quad \sum\limits_{i,j} \{a_{ij}\kappa_l^-(i,j) - b_{ij}\kappa_l^+(i,j)\} \geq 0 \\
\quad \forall \text{ edges } e : \pi_l(e) \geq 0 \\
\quad \forall \text{ pairs } i \to j : w_l(i,j) \geq 0, \kappa_l^+(i,j) \geq 0, \kappa_l^-(i,j) \geq 0 \\
\quad \forall \text{ nodes } i : w_l(i,i) = 0, \kappa_l^+(i,i) = 0, \kappa_l^-(i,i) = 0
\end{array} \tag{4.17}$$

Usually a failure restoration approach like reoptimization and augmentation causes routing disruptions. An arc-routing may introduce a high degree of routing disruptions for failure restoration. MORE may restrict the routing disruptions, since it is a multipath approach. Moreover, simulation results in Section 4.5 demonstrate that MORE is robust to link failures and routing changes. Thus, for MORE, reoptimization and augmentation may provide affordable performance with respect to potential routing disruptions.

Since a link in a PoP-level topology may represent many physical links, 20% capacity reduction of PoP links is studied, in an attempt to study reasonable failure scenarios. All the cases in which one or two links lose 20% of the capacity are studied, with a base TM using the Gravity model and $w = 2.0$. Then the cumulative distribution of the oblivious ratios of all these failure cases is computed. For example, in Figure 4.5, for AS 3967 with nochange, more than 50% of the failure cases result in an oblivious ratio smaller than 1.40.

Figure 4.5 shows that augmentation has a similar performance to reoptimization. Augmentation is supposed to optimize the oblivious ratio only for the affected OD pairs. A suspicion is that most OD pairs have been affected by the link failures, so that augmentation performs similar to reoptimization. However, a more careful checking of the results shows that there are indeed some portion of OD pairs that are not affected by the failures. That is, augmentation does optimize for the affected OD pairs only, but not for most OD pairs, or all the OD pairs as reoptimization. Even for nochange with the routing, for a large fraction of failure cases, the 20% capacity reduction may not increase the oblivious ratio significantly.

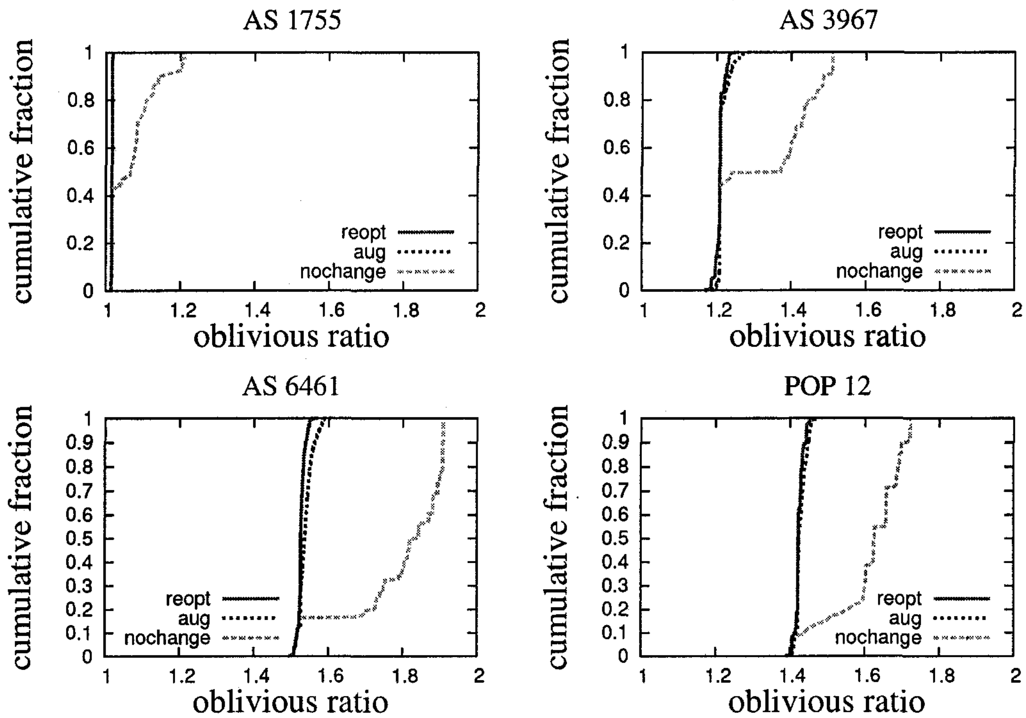


Figure 4.5: Cumulative distribution of the oblivious ratios, when one- or two-link failure (20% capacity reduction) happens.

The analysis on link failure can also be used to improve the network provisioning: for example, for those links whose 20% capacity reduction cause large oblivous ratio increases, adding 25% of the link capacity will maintain a low oblivious ratio when a 20% capacity reduction failure happens.

Simulation results in Section 4.4.5 show the robustness of MORE over link failures. It is desirable to further study more severe failures, e.g., whole link or node failures as in [7].

4.4.4 Adversary attack

An attack is introduced which can exploit a routing **f**, by generating a TM that causes **f** to incur a high MLU. An experimental study will show that an oblivious routing is robust to such an attack. However, an adaptive routing may suffer much higher MLU.

Such an attack works as follows. For a given arc-routing $\mathbf{f}$,[7] LP (4.18) computes the traffic demand $\mathbf{d}$ that gives the MLU on edge l, assuming there is a range restriction $0 \leq a_{ij} \leq d_{ij} \leq b_{ij}$. Then the adversary demand is the demand that gives the largest MLU over all edges. LP (4.18), called the "adversary LP", is based on the work in [8]. To obtain the LP formulation when there is no knowledge of the traffic, i.e., no range restriction, remove the constraints $\forall$ demands $i \rightarrow j : d_{ij} - \lambda b_{ij} \leq 0, -d_{ij} + \lambda a_{ij} \leq 0$ and $\lambda \geq 0$.

$$
\begin{array}{l}
\max\limits_{d,g,\lambda} \sum\limits_{ij} d_{ij} f_{ij}(l)/cap(l) \\
\forall \text{ pairs } i \rightarrow j : \sum\limits_{e \in out(j)} g_i(e) - \sum\limits_{e \in in(j)} g_i(e) + d_{ij} \leq 0 \\
\forall \text{ edges } e : \sum\limits_{i} g_i(e) \leq cap(e) \\
\forall \text{ demands } i \rightarrow j : d_{ij} - \lambda b_{ij} \leq 0 \\
\forall \text{ demands } i \rightarrow j : -d_{ij} + \lambda a_{ij} \leq 0 \\
\forall \text{ nodes } i, \text{ edges } e : g_i(e) \geq 0, \lambda \geq 0
\end{array}
\tag{4.18}
$$

In the following experiments, MORE is compared with an adaptive arc-routing, denoted as *adaptive-arc*, which computes an optimal arc-routing for a given TM. The experiments run in iterations. The Gravity model is used to set $\mathbf{TM}_0$. In iteration 1, adaptive-arc computes an optimal routing $\mathbf{f}_1$ for demand $\mathbf{TM}_0$. Before iteration 2, the attacker computes the adversary demand $\mathbf{TM}_1$ for routing $\mathbf{f}_1$. In iteration 2, routing $\mathbf{f}_1$ is used for the demand $\mathbf{TM}_1$, thus it incurs high MLU/OPT, the MLU compared with an optimal. In Iteration 3, adaptive-arc computes an optimal routing $\mathbf{f}_2$ for $\mathbf{TM}_1$. In Iteration 4, the adversary attacker computes the adversary demand for $\mathbf{f}_2$, and activates it. And so on. Thus, on the odd iterations, adaptive-arc will have MLU/OPT=1, but on even iterations, it will have a higher MLU/OPT. MORE keeps the routing unchanged.

Figure 4.6 shows how MORE and adaptive-arc perform when there is an adversary attack. The left column shows the results when there is no restriction on the demand, i.e., $w = \infty$. Adaptive-arc may have a very large MLU/OPT, when it suffers from the attack. The y-axis is truncated at MLU/OPT=100.0, with a log scale. The right column shows the results when the error margin $w = 2.0$. The ratios of corresponding oblivious routings are shown as the horizontal straight lines.

Figure 4.6 shows that the adversary attack can exploit an adaptive routing, and make MLU/OPT prohibitively high. However, MORE is robust to the attack. The oblivious ratio predicts its worst performance. An oblivious routing can be viewed as an optimal equilibrium point in a game in which a network operator combats with all possible adversary traffic demands (within the range restriction when it is stipulated). This shows the robustness of MORE against the adversary attack, and the potential vulnerability of an adaptive routing. The results also show that MORE can perform better than what the oblivious ratio predicts, i.e., the curve of MORE is sometimes below the straight line for the ratio.

[7] For a path-routing, convert it to an arc-routing first. Alternatively, LP (4.9) can compute an adversary.

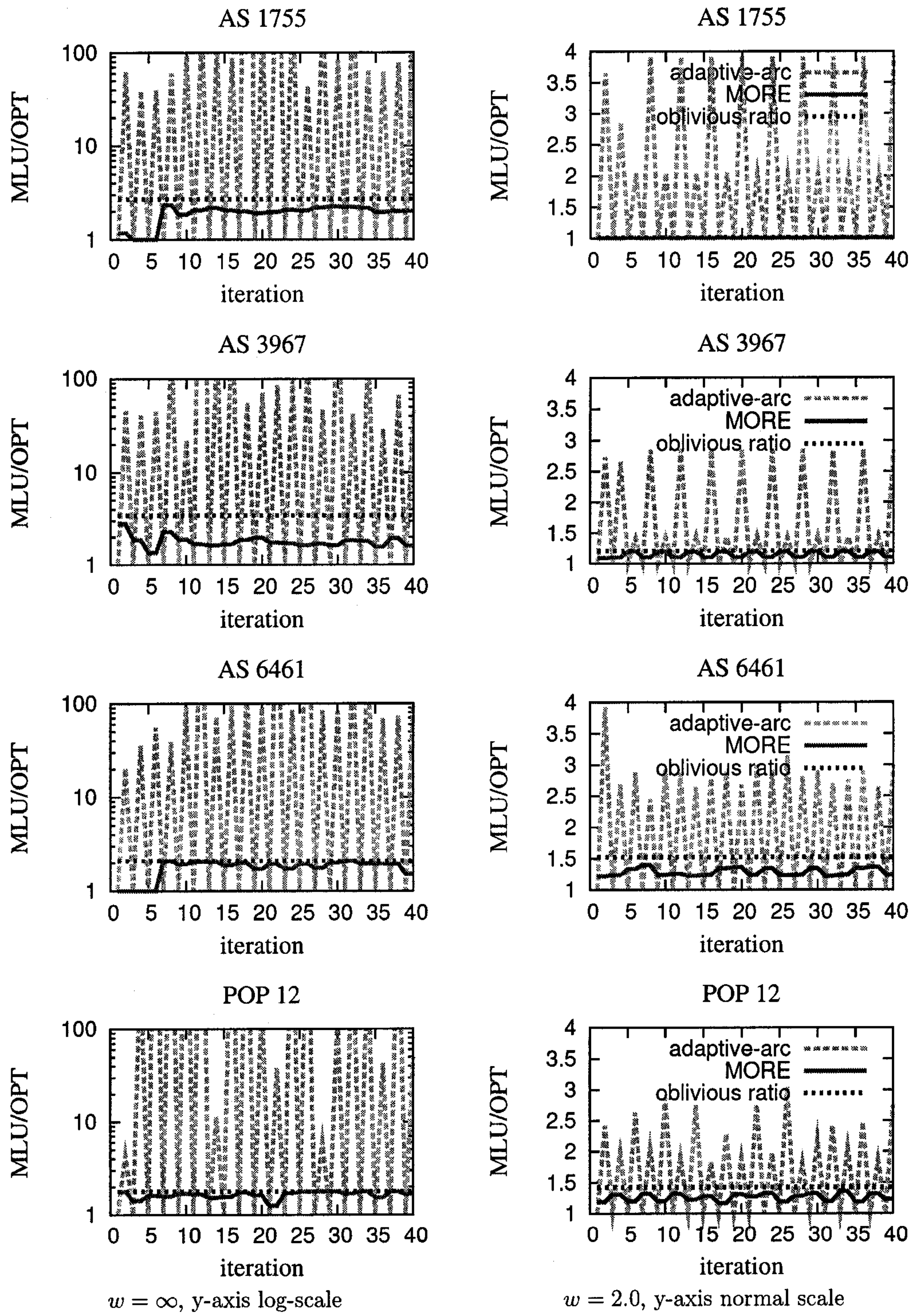


Figure 4.6: Comparing MORE with adaptive-arc under adversary attack. **Legend**: in figures on right column.

4.4.5 Simulation

In this section, the performance of MORE is studied using packet-level simulation with NS2 [3]. The robust weighted hashing by Ross [54] is implemented, so that traffic can be split into multiple paths according to the routing fraction of each path. Either the Gravity model or the Lognormal model is used to generate synthetic TMs. Then, according to the synthetic TMs, Pareto On/Off traffic[8] is generated to obtain variability in the actual traffic. Note that although a TM may not change, traffic varies due to the Pareto distribution. The link utilization is averaged for every 0.5 second simulated interval to obtain MLU.

Varying TMs and routings. MORE is a quasi-static solution, it may have to change the routing when necessary. Simulation is used to attempt to study the performance of MORE over changing TMs and routings. Ten Lognormal TMs [47] are generated. Each TM lasts 10 simulated seconds. MORE computes an optimal multipath oblivious routing for a given TM with error margin $w = 2.0$. Thus, for MORE, there are potentially different routings for different TMs. Adaptive$K$ computes an optimal routing with K-shortest paths for each TM, with $K = 20$. MORE and Adaptive$K$ may have different sets of paths for each OD pair. Assume both MORE and adaptive$K$ know a new TM instantaneously and reoptimize the routing for the new TM instantaneously. Adaptive$K$ represents an adaptive scheme on K-shortest paths that can respond to traffic changes without any delay, i.e., it is an unachievable best case for adaptive schemes.

Results are shown in Figure 4.7.[9] The TMs are scaled, so that optimal arc-routings of these TMs have the same MLU. The results show that MORE incurs similar MLUs over varying TMs and routings, and MORE achieves similar performance to adaptive$K$.

TeXCP[10] vs. MORE. MORE is compared with TeXCP, an adaptive multipath routing approach [27]. TeXCP collects network load information and adjusts routing fractions on pre-selected multiple paths for each OD pair to balance the network load. TeXCP also uses MLU as the performance metric. For comparison with TeXCP, link capacity is set in a way similar to [27], i.e., links with high-degree nodes have large capacity and links with low-degree nodes have small capacity. The parameters for TeXCP are set as suggested in [27], e.g., 10 shortest paths are used for each OD pair. Traffic is generated according to a Gravity TM. During time intervals $[25, 50]$ and $[75, 100]$, an extra TM is activated, so that extra traffic is generated for each OD pair.

Figure 4.8 shows the comparison results. The results are shown after 10 seconds, so that TeXCP may have passed the "warm-up" phase. Both TeXCP and MORE respond to the

[8] In Pareto On/Off traffic, packets are generated according to a Pareto On/Off distribution. Packets are generated at a fixed rate during on periods, and no packets are generated during off periods. On and off periods follow a Pareto distribution. Packets are of a constant size.

[9] For Figure 4.7 and 4.10, there are downward spikes for both adaptive$K$ and MORE. These are due to the transition of stopping and starting TMs.

[10] TeXCP is implemented by Baochun Bai, a PhD student in our department.

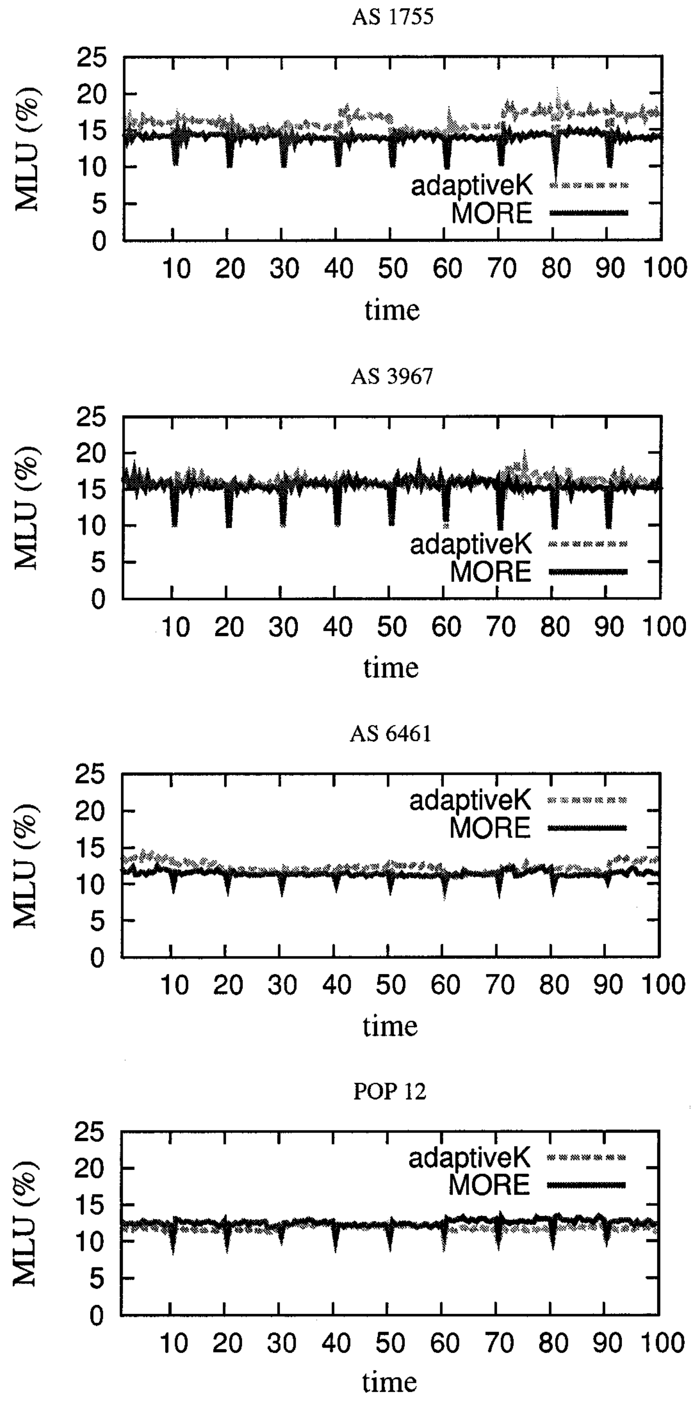


Figure 4.7: Excellent performance of MORE over varying TMs and routings. For each 10 seconds, a random TM is generated, and MORE responds with an optimal multipath oblivious routing over the same set of paths. For adaptive$K$, it computes, for each TM, an optimal routing on K-shortest paths ($K = 20$).

traffic increases. The results show that MORE has a comparable performance to TeXCP. When TeXCP is in the transition of adapting to its optimal routing, MORE may have better performance, e.g. in the time interval [25, 50] for POP 12. However, TeXCP may adapt to a better routing than MORE, e.g., in the time interval [75, 100] for AS 3967. MORE, being oblivious to traffic changes, saves resources consumed by TeXCP for frequently collecting network information. With a longer time period (35 seconds) for the "warm-up", TeXCP has similar performance.

Link failure. The robustness of MORE over link failures is studied in Section 4.4.3 using numerical studies. It is studied using simulation here. At each 10 seconds, a random link failure occurs with 20% POP link capacity reduction. After each link failure, the augmentation strategy with $w = 2.0$ for failure restoration is used to optimize the oblivious routing for the affected paths. The traffic is kept unchanged, generated according to a Gravity TM. Figure 4.9 shows that the networks have rather stable performance, after several consecutive link failures. Reoptimization has similar performance.

Adversary attack. Section 4.4.4 studies the performance of MORE and adaptive-arc under an adversary attack using numerical studies. The performance of MORE and adaptive$K$ under an adversary attack is studied here using simulation.[11] Adaptive$K$ computes an optimal routing on K-shortest paths ($K = 20$) for a given TM. An adversary attack can exploit an adaptive routing for the last TM, by generating a new TM. MORE does not change the routing, for either paths or routing fractions.

The simulation runs in iterations, each 10 seconds in duration. In the first iteration, adaptive$K$ encounters an adversary attack; while in the second iteration, it uses the optimal routing for the adversary in the first iteration. In the third iteration, the adversary attacks again; while in the fourth iteration, adaptive$K$ responds with an optimal routing for the adversary in the third iteration. And so on. Thus, on the odd iterations, adaptive$K$ will have a higher MLU, but on even iterations, it will have the optimal MLU. Assume adaptive$K$ can know the exact TM, and deploys the new optimal routing instantaneously in the beginning of an even iteration.

The results are shown in Figure 4.10. It shows that when adaptive$K$ is under the adversary attack, it has much larger MLU than MORE. However, when adaptive$K$ operates in optimal, its performance is comparable to MORE mostly, so that their curves overlap. Sometimes adaptive$K$ performs slightly better than MORE, e.g., during time [50, 60] for AS 6461. The results show that, MORE is robust under an adversary attack, and it has a performance close to adaptive$K$ when adaptive$K$ is not under attack.

[11] Adaptive$K$ responds to traffic changes instantaneously, while TeXCP takes time for convergence, thus MORE is not compared with TeXCP for the study on adversary attack.

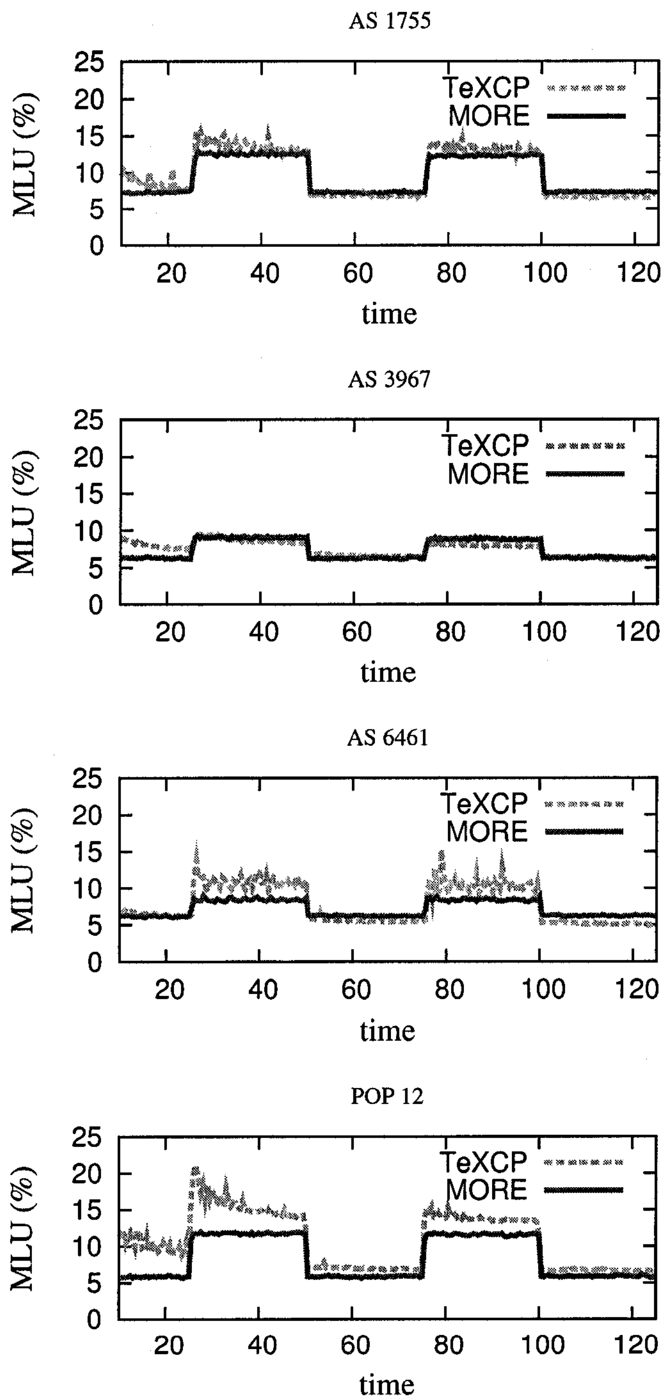


Figure 4.8: TeXCP vs. MORE. During time interval [25,50] and [75,100], extra random traffic is generated.

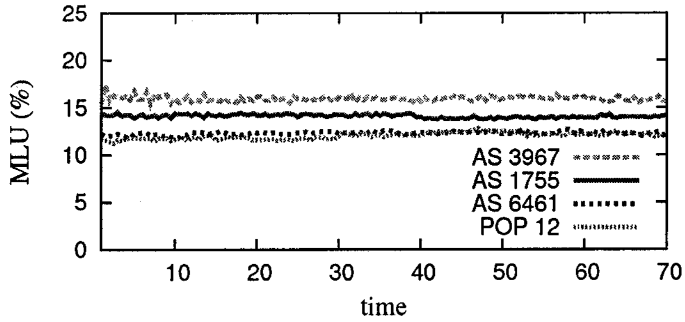


Figure 4.9: Robustness of MORE over failures. At each 10's second, a random link failure occurs, and MORE uses the augmentation strategy for failure restoration over the same set of paths. The TM does not change.

4.5 Implementation and Deployment Issues

MORE is a quasi-static solution, so that it is not responsive to traffic dynamics on a small time scale. Armed with recent achievements in traffic estimation, we are confident with adjusting an oblivious routing on an hourly, multi-hourly or even daily basis. However, routing adjustments are necessary when severe failures occur or if enhancements of the performance are desirable.

Adjustments are necessary if the current traffic deviates much from the last estimation. Traffic estimation techniques such as those in [61, 70] can be leveraged. In contrast to the frequent collection of network information for an adaptive approach, a large time-scale traffic estimation is sufficient for MORE. Traffic estimation entails information about the traffic across the network. However, the data for traffic estimation, e.g. Simple Network Management Protocol (SNMP) data, are available from routine network management tasks [70], so that no extra network devices or software is needed.

With routing adjustments, there is an issue of how to mitigate potential routing disruptions. An approach is to exploit the robust weighted hashing [54], which claims the least service disruption when failures occur. Simulation results show that MORE is robust under varying routings due to traffic changes (Figure 4.7) and link failures (Figure 4.9), with the robust weighted hashing [54] for flow-based multipath routing. Further improvements may be achieved by exploiting the traffic burstiness, as studied recently in [60].

MORE provides an efficient implementation of oblivious routing and is amenable to gradual deployment. MORE needs to centrally compute the routing and to set up the routing at edge routers. Then an edge router splits incoming traffic according to the routing fractions. MORE does not need to collect instantaneous network information. Thus, there is no need to change the core routers. This also eases the management and operation of the deployment of MORE.

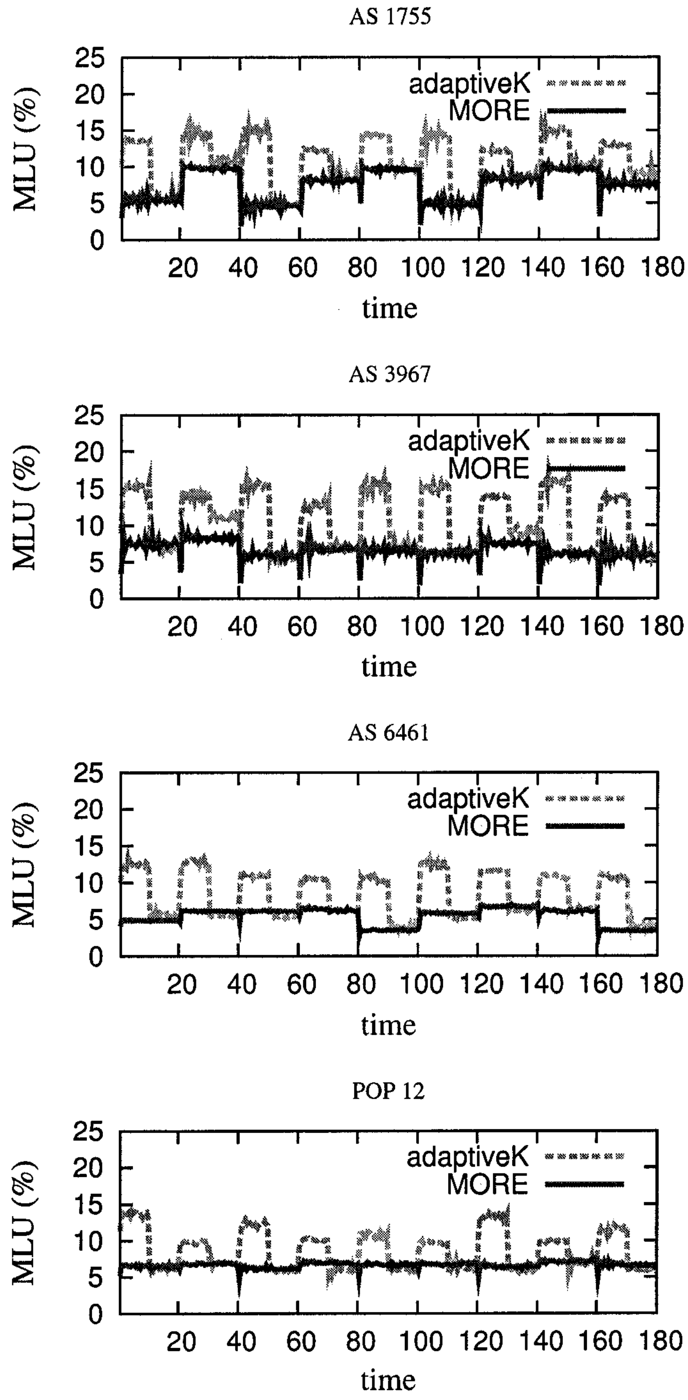


Figure 4.10: Adaptive$K$ vs. MORE. During each iteration (20 seconds), for the first half, adaptive$K$ encounters an adversary attack; while for the second half, adaptive$K$ operates with an optimal routing. MORE does not change the routing over the whole run of the simulation.

MORE is proposed for intra-domain traffic engineering. Further investigation is needed for its operation for inter-domain traffic engineering. The current Internet uses OSPF for intra-domain routing and Border Gateway Protocol (BGP) for inter-domain routing. With the OSPF/BGP scheme, end-to-end connections can be established over multiple domains. Further study of MORE may follow the OSPF/BGP scheme, and it will play the similar role to OSPF within an domain.

4.6 Conclusions

A promising approach for stable and robust intra-domain traffic engineering with changing and uncertain traffic demands has been investigated. MORE, a multipath implementation of demand-oblivious routing [8], is presented. The performance of MORE has been evaluated by both numerical and simulation studies. The performance study shows that MORE can obtain a close multipath approximation to [8]. The results also show the excellent performance of MORE under varying traffic demands, link failures and an adversary attack.

This research opens the door for a viable deployment of oblivious routing, thus an intra-domain traffic engineering technique robust to changing and uncertain traffic demands.

Chapter 5

Network Flow in Multihop Wireless Networks

In this and the next chapters, the issue of energy efficiency in multihop wireless networks with changing and uncertain traffic demands will be addressed. In this chapter, definitions and formulations will be presented. Some were presented in our published papers [35, 38], including the energy consumption model, the definitions of energy utilization, maximum energy utilization, minimax (optimal) energy utilization, competitive analysis framework and formulations for lossy links. Some are based on previous work by others, including the linear expressions for schedulability constraints. This chapter provides the background for the next chapter, where LP formulations for traffic-oblivious energy-aware routing will be presented and their performance will be evaluated.

5.1 Introduction

A multihop wireless network may be a wireless ad hoc network, in which the network is formed in an ad hoc manner, a wireless sensor network, in which the network consists of sensors communicating with each other by wireless transmissions, a wireless mesh network, which may be deployed in a community with fixed topology, or a wireless network of stationary base stations. The "multihop" is in contrast to the single hop cellular networks where mobile devices can communicate directly to base stations.

Chapter 2 presents background materials for network flow theory, of which some are applicable to wireline networks only. To apply network flow theory to problems in wireless networks, several issues need consideration. Energy efficiency is a paramount issue when energy sources are costly or there are energy constraints. With accurate knowledge of traffic demands, optimizing energy efficiency can be modeled as a linear program [14]. It is desirable to optimize energy efficiency with changing and uncertain traffic demands. The energy consumption model and the metrics for energy efficiency will be presented. Wireless networks have unique features such as lossy links and interference. Lossy links affect energy efficiency due to retransmissions and broadcasting. With the presence of interference, a flow may not be achievable. How to address the concerns with loss and interference within an LP formulation will be discussed.

First the network model for multihop wireless networks is discussed. Assume the network topology is stationary. A stationary multihop wireless network can be abstracted as a digraph $G = (V, E)$, where V is the set of wireless nodes and E is the set of "edges". A transmission signal fades as it travels farther away. There is an edge from u to v if the distance between them is less than the "threshold" that u can transmit packets successfully to v. The distance between u and v is denoted as $dist(u, v)$. A digraph is a directed graph. Assume the digraph is strongly connected. An edge has a bandwidth or capacity $c(s, t)$, i.e., the data rate it can support. Each node u has an initial energy level $pow_0(u)$.

As in Chapter 2, $in(u)$ and $out(u)$ are used to denote the sets of edges "into" and "out of" node u respectively, i.e., $in(u) = \{(t, u)|(t, u) \in E\}$, and $out(u) = \{(u, v)|(u, v) \in E\}$. $out(v, -u)$ denotes the set of edges out of v, excluding (v, u), i.e., $out(v, -u) = \{(v, w)|(v, w) \in E, w \neq u\}$.

5.2 Related Work

Previous work on energy efficiency has made great progress. Ephremides [17] and Goldsmith and Wicker [23] give surveys on energy concerns.

Singh et al. [59] investigate power-aware routing in wireless ad hoc networks. They propose several routing metrics and study their performance through simulation. Shortest paths computed with such weights may create "bottleneck" nodes, such that these nodes run out of energy quickly.

A good load balancing technique is necessary for energy efficiency. The network flow techniques provide solutions for load balancing. The problem of maximizing the lifetime of a wireless ad hoc network with energy constraints is studied in [14, 33], where the lifetime is defined as the length of the time until the first node drains out its energy. It assumes every node is important. This research adopts this model. Kar et al. [28] investigate how to route the maximal number of messages in wireless ad hoc networks with energy constraints. Sadagopan and Krishnamachari [56] study the problem of maximizing data extraction in wireless sensor networks with energy constraints. If the power supply is renewable, it is desirable that the energy consumption rate is less than the renewal rate. Lin et al. [39] study power-aware routing with renewable energy sources.

Some previous work assumes exact prior knowledge of traffic demands, e.g. [14, 56]. The traffic demands may be known a priori in some applications, such as in a wireless sensor network in which sensors periodically report weather information. With knowledge of the traffic demands, network flow [4] can be used to model the energy efficiency problem. Chang et al. [14] model the problem of lifetime maximization as a linear program (LP) and give a heuristic solution. Sadagopan and Krishnamachari [56] develop an approximate algorithm and a heuristic algorithm based on an LP formulation of the data extraction problem. In this work the optimal routing is studied in the *minimax* sense, i.e., to minimize the maximum energy utilization, in multihop wireless networks. Given the traffic demands, the problem to minimax energy utilization can be modeled as an LP optimization problem.

A routing scheme may be adaptive to the traffic demands and the network condition [28, 33, 39]. The approach in [33] needs a regular, e.g. cyclic, traffic demands to achieve the performance guarantee. The adaptive approaches in [28, 39], which are based on the work of adaptive routing in a wired network [50], have performance guarantees that are logarithmic in network size. An adaptive approach usually needs ongoing collection of network information, e.g., the remaining energy level of each node. It is desirable to design an efficient scheme to collect necessary information for energy efficiency with respect to both computing an energy-efficient route and economizing energy for information collection.

The research on oblivious routing in optimizing link utilization (congestion) [8, 10, 53] has made great achievements, as surveyed in Section 4.2. This work is the first study on oblivious routing in wireless networks, in particular, the energy efficiency problem.

A wireless network has unique features, such as interference and dynamic channel conditions, in contrast to a wired network. Recently there is increased interest in jointly considering routing and scheduling. Schedulability of a routing is studied in Hajek and Sasaki [24] and Kodialam and Nandagopal [30] for the "free of secondary interference" model, where a node can transmit to or receive from at most one node. Necessary and sufficient conditions are derived. Jain et al. [26] use a conflict graph to model the interference relationship between links and investigate lower and upper bounds of an achievable network flow. On the other hand, emerging technologies, e.g. the orthogonal frequency division multiplexing ultra wideband (OFDM-UWB) system [46], may create an "interference-free" wireless environment which renders schedulability of a routing no longer a (serious) problem.

5.3 Energy Efficiency in Multihop Wireless Networks

In the following, first the energy consumption model will be discussed. Then comes the discussion of maximum energy utilization and optimal routing with accurate traffic demands. Next oblivious routing for energy efficiency will be discussed.

5.3.1 Energy Consumption Model

The energy consumption to transmit a unit amount of data from node u to another node v is $tx(u, v)$. Usually $tx(u, v)$ depends on the distance between u and v. The amount of energy consumption in transmission is proportional to the amount of data to be transmitted. This

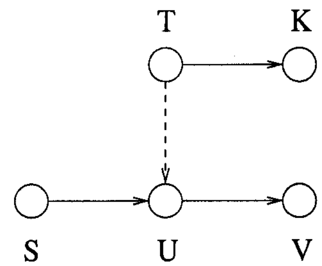


Figure 5.1: An example: energy consumption model

linear model is used in previous work on energy efficiency, e.g. [14, 25, 28, 33, 56, 57].

The energy consumption of node u to receive and to overhear a unit of message are denoted as $r(u)$ and $h(u)$ respectively. Overhearing means a node receives a packet not addressed to it. Reception and overhearing are separated since they may consume different amounts of energy. For instance, a node may overhear the whole data packet or only the preamble before discarding it. In the former case, overhearing consumes a similar amount of energy as reception; while in the latter overhearing may consume much less energy. The energy consumption for processing data may be a component of the transmission model and the reception model, thus it is not modeled explicitly.

Figure 5.1 illustrates the energy consumption model for node U. Node U consumes energy for three actions: the transmission to node V, the reception for the transmission from node S to itself, and the overhearing for the transmission from node T to node K.

The energy consumption of node s for d_{ij} is,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{(s,t)\in out(s)} \{d_{ij} f_{ij}(s,t) tx(s,t)\} \\ & + \sum_{(t,s)\in in(s)} \{d_{ij} f_{ij}(t,s) r(s)\} \\ & + \sum_{(t,s)\in in(s)} \sum_{(t,k)\in out(t,-s)} \{I_{(t,s)}^{(t,k)} d_{ij} f_{ij}(t,k) h(s)\} \end{aligned} \tag{5.1}$$

$I_{(t,s)}^{(t,k)}$ is an indicator function defined as,

$$I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } s \text{ can overhear transmission from } t \text{ to } k; \\ 0 & \text{otherwise.} \end{cases} \tag{5.2}$$

The first term in $\text{energy}_s(i,j)$ is the energy consumption for transmission; the second for reception and the third for overhearing. $I_{(t,s)}^{(t,k)}$ is used to indicate that if node s is within the transmission range of the transmission from t to k, s can overhear the transmission and consumes energy for the overhearing. Chang et. al. consider only the energy consumption for transmission [14]. Sadagopan and Krishnamachari [56] consider energy consumption for both transmission and reception. The energy consumption for overhearing is also considered here. The total energy consumption for node s is,

$$\textbf{energy}_s = \sum_{i,j} \text{energy}_s(i,j) \tag{5.3}$$

Energy consumption model $\text{energy}_s(i,j)$ and $\mathbf{energy}_s$ are linear functions of the routing $\mathbf{f}$. The routing variable is omitted for brevity.

Generalization

The energy consumption model $\mathbf{energy}_s$ (5.3) is general enough to take into account several issues in radio transmission. By properly defining the indicator function, we can handle the case in which a node can vary its transmission range with arbitrary precision, at several discrete levels, or with a fixed transmission range. Note a node may transmit on different links with different power; but the power on a link is assumed constant.

For example, assume a disk model for radio transmission, i.e., the maximum transmission range is the same in all directions. Also assume omni-directional transmission. When a node can vary its transmission range with arbitrary precision, the indicator function is,

$$I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } dist(t,k) \geq dist(t,s); \\ 0 & \text{otherwise.} \end{cases}$$

When there are n_t transmission ranges for a wireless node t, $r_1, r_2, ..., r_{n_t}$, with $r_1 < r_2 < ... < r_{n_t}$, $dist(t,k)$ is replaced with r_i, where $r_i \geq dist(t,k)$, and if $i \neq 1$, $r_{i-1} < dist(t,k)$. That is, $dist(t,k)$ is replaced with the smallest transmission range which is $\geq dist(t,k)$. The indicator function is,

$$I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } r_i \geq dist(t,s); \\ 0 & \text{otherwise.} \end{cases}$$

In the case where the transmission range for node t is fixed, denoted as $TxR(t)$, we can obtain the proper indicator function by replacing r_i with $TxR(t)$.

As well, the model can handle the radio irregularity problem studied recently, e.g. in [65], that a radio has different maximum transmission ranges in different directions. This affects the neighborhood relationship. The energy model can be used for the wireless communication using either an omni-directional antenna or a directional antenna. For a directional antenna, the model for transmission $tx(s,t)$ and reception $r(s)$ need to include a component to account for the energy consumption for managing the antenna.

5.3.2 Maximum Energy Utilization

A performance metric, *maximum energy utilization* is introduced; and based on it, the energy efficiency problem is modeled as an LP optimization problem. The definition of this metric is inspired by the derivation of the maximum lifetime, e.g. in [14] and the definition of the maximum link utilization, e.g. in [8]. With this metric, more problems besides lifetime maximization can be handled.

A *routing* $\mathbf{f}$ specifies what fraction of the traffic for each OD pair is routed on each edge, as defined in (2.4). For a given routing $\mathbf{f}$ and a given traffic matrix $\mathbf{tm}$, the maximum energy utilization (MEU) measures the "goodness" of the routing. The lower the maximum energy utilization, the better the routing.

$$\text{MEU}(\mathbf{tm}, \mathbf{f}) = \max_s \frac{\mathbf{energy}_s}{pow_0(s)} \tag{5.4}$$

5.3.3 Minimax Energy Utilization

Given **tm**, the *optimal routing* minimizes the maximum energy utilization:

$$\text{OPTE}(\mathbf{tm}) = \min_{\mathbf{f}:\mathbf{f} \text{ is a routing}} \text{MEU}(\mathbf{tm}, \mathbf{f}) \tag{5.5}$$

The minimax energy utilization measures the energy consumption rate of a wireless network. It can be regarded as a unification of several studied problems: lifetime maximization with or without energy renewal, maximization of the number of messages or data extraction, and minimization of power consumption. The lifetime of a wireless network is inversely proportional to the energy consumption rate of the node that consumes energy the fastest. For a given traffic matrix, once we minimax the energy utilization, we effectively maximize the lifetime of the multihop wireless network. The problem of minimizing the renewal rate can be dealt with similarly. Minimaxing energy utilization is equivalent to maximizing data extraction according to the data rates of the sources, which is a concurrent multicommodity problem [4]. When wireless nodes have the same initial power reserve, minimaxing energy utilization is equivalent to the problem of minimizing power consumption.

Given a traffic matrix, the optimal routing to minimax energy utilization is solvable as an LP multi-commodity flow problem [4]. For now, only routing is considered, and consideration for schedulability of a routing is deferred until Section 5.4. The LP to find the optimal routing follows, with routing **f** and η as variables:

$$\begin{array}{l} \min_{\eta, f} \eta \\ \mathbf{f} \text{ is a routing} \\ \forall \text{ nodes } s : \mathbf{energy}_s / pow_0(s) \leq \eta \end{array} \tag{5.6}$$

LP (5.6) minimizes the maximum energy utilization for a given traffic matrix, i.e., LP (5.6) is equivalent to $\min_{\mathbf{f}} \text{MEU}(\mathbf{tm}, \mathbf{f})$. This LP is similar to that of Chang et al. [14] for maximizing the lifetime of a wireless ad hoc network.

For an application with prior knowledge of the traffic demands, the above LP model is sufficient to compute the optimal routing to minimax energy utilization. For example, it maximizes the lifetime of a wireless sensor network that periodically reports weather information.

5.3.4 Competitive Analysis

The routing computed by LP (5.6) does not guarantee performance for other traffic matrices. LP models will be developed to compute the optimal routing that achieves minimax energy utilization with a weak assumption on the traffic demands. First the metric of competitive ratio is introduced that follows the competitive analysis [8, 50], similar to that in Section 2.4.2 for link utilization in the Internet.

For a given routing **f**, a given traffic matrix **tm**, the *competitive ratio* is defined as the ratio of the maximum energy utilization of the routing **f** on the traffic matrix **tm** to the maximum energy utilization of the optimal routing. Competitive ratio measures how far the routing **f** is from the optimal routing on the traffic matrix **tm**. Formally,

$$\mathrm{CR}(\mathbf{f}, \{\mathbf{tm}\}) = \frac{\mathrm{MEU}(\mathbf{tm}, \mathbf{f})}{\mathrm{OPTE}(\mathbf{tm})} \tag{5.7}$$

The competitive ratio is usually greater than 1. It is equal to 1 only when the routing **f** is an optimal routing for **tm**. When we are considering a set of traffic matrices **TM**, the competitive ratio of a routing **f** is defined as,

$$\mathrm{CR}(\mathbf{f}, \mathbf{TM}) = \max_{\mathbf{tm} \in \mathbf{TM}} \mathrm{CR}(\mathbf{f}, \mathbf{tm}) \tag{5.8}$$

The competitive ratio with respect to a set of traffic matrices is usually strictly greater than 1, since a single routing usually can't optimize energy utilization over the set of traffic matrices.

When set **TM** includes all possible traffic matrices, $\mathrm{CR}(\mathbf{f}, \mathbf{TM})$ is referred to as the *oblivious competitive ratio* of the routing **f**. This is the worse competitive ratio the routing **f** achieves with respect to all traffic matrices. An *optimal oblivious routing* is the routing that minimizes the oblivious competitive ratio. Its oblivious ratio is the *optimal oblivious ratio* of the network.

Suppose there is an oracle that knows the current traffic matrix **tm** and computes its optimal routing with energy utilization e. The energy utilization of the optimal oblivious routing for **tm** is guaranteed to be within $[e, r * e]$, where r is the oblivious ratio. It may achieve lower energy utilization than $r * e$ for the particular traffic matrix **tm**. The oblivious routing guarantees the performance of what an oracle can achieve multiplied by the oblivious ratio for all traffic matrices.

5.4 Background: Schedulability of a Routing

In wireless communications, transmissions may interfere with each other so that signals may be garbled. As a result, a flow achievable in a wireline counterpart may not be achievable in a wireless network. In Figure 5.2, a throughput of $15/3 = 5Mbps$ is achievable from A to D on path $ABCD$. It follows a schedule of allocating a slot for each of the three links on the path, AB, BC and CD. However, on path ABD, only $15/4 = 3.75Mbps$ is achievable. Note, on path $ABCD$, when link CD is active, link AB can not be active, since the overhearing at B of the transmission on link CD garbles the transmission on link AB.

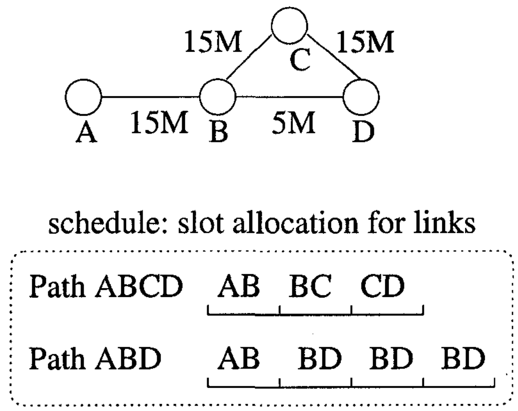


Figure 5.2: The topology and the transmission schedules

First the interference-free scenario will be discussed. When the traffic load is relatively low compared with the bandwidth, the interference is less severe or negligible. With the emerging orthogonal frequency division multiplexing ultra-wideband (OFDM-UWB) radio technology [51], a wireless node has a wide bandwidth, which may result in a large number of orthogonal channels between a pair of nodes; at the same time, the power is limited, thus the traffic load is low compared to the large bandwidth. Consequently, concurrent transmissions may be arranged in a manner such that there is negligible interference. This "interference-free" feature of UWB is exploited in [46]. In some applications, such as some sensor networks, traffic may be sporadic. Interference may not be a major concern in such cases. Note that in a network with low traffic load, a certain load/energy balancing technique is still needed for energy efficiency.

In an interference-limited wireless network, it is necessary to consider schedulability of a routing. To optimize a schedulable routing is essentially to solve an optimization problem at the intersection of the feasible flow space and the feasible schedule space. Researchers seek necessary and sufficient condition for a flow to be schedulable. In the problem to maximize network flow (throughput), researchers look for lower and upper bounds for the schedulable flow. This work usually assumes a TDMA/CDMA scheduling scheme.

TDMA and CDMA are two scheduling schemes at the medium access control (MAC) layer in wireless transmission. In TDMA, Time Division Multiple Access, the radio spectrum is divided into time slots, and in each slot, only one node is allowed to either transmit or receive. Here, TDMA uses time division duplexing (TDD) rather than frequency division duplexing (FDD). In CDMA, Code Division Multiple Access, simultaneous transmissions can be separated using spread spectrum techniques. In a TDMA/CDMA scheme, time can be divided into slots. Within each slot, simultaneous transmissions are possible. However, at any time slot, a radio can either transmit to or receive from at most one other radio.

The free of secondary interference model [11], where a node can transmit to or receive from at most one node at a time, receives considerable attention.[1] Hajek and Sasaki [24] investigate the polynomial complexity of the schedulability of a routing with the Ellipsoid method [49], which is impractical. Kodialam and Nandagopal [30] give necessary and sufficient conditions, as linear constraints over the flows and data rate on neighboring edges of a node. The necessary and sufficient conditions can be expressed as follows for each node s when β takes the values of 1 and $\frac{2}{3}$ respectively:

$$\forall \text{ nodes } s, \sum_{(s,t)\in out(s)} \sum_{i,j} \frac{g_{ij}(s,t)}{c(s,t)} + \sum_{(t,s)\in in(s)} \sum_{i,j} \frac{g_{ij}(t,s)}{c(t,s)} \leq \beta. \tag{5.9}$$

Jain et al. [26] introduce a "conflict graph" to model the interference relationship between links. In the conflict graph, a vertex represents a link in the connectivity graph. There is an edge between two vertices in the conflict graph if the two corresponding links in the connectivity graph interfere with each other. They consider two interference models. In the protocol interference model, a transmission is successful if the receiver is within the transmission range of the transmitter and any node within its interference range does not transmit. In the physical interference model, a transmission is successful if the signal-to-noise ratio (SNR) at the receiver exceeds a threshold, where SNR is determined by the ambient noise of the receiving node and the interference due to other ongoing transmissions. They study the lower and upper bounds on the achievable network flow (throughput). For the lower bound, independent sets (in which there is no edge for any two vertices) in the conflict graph are used to add constraints to the space of feasible network flows so that the resulting flow is schedulable. First find K maximum independent sets, $I_i, 1 \leq i \leq K$. Let λ_i denote the fraction of time allocated to independent set I_i.

$$\sum_{i=1}^{K} \lambda_i \leq 1 \text{ and } \sum_{i,j} g_{ij}(s,t) \leq \sum_{(s,t)\in I_i} \lambda_i c(s,t) \tag{5.10}$$

The first constraint requires that only one independent set can be active at a time. The second requires that the flow can not exceed the convex combination of edge capacities in the independent sets. Although it is hard to obtain all the independent sets to make the lower bound tight, the bound gets tighter with more independent sets [26].

Wu et al. [66] introduce the "elementary capacity graph", which represents a group of edges that are active simultaneously. An elementary capacity graph is equivalent to the independent set on a conflict graph in [30]. A capacity graph is a convex combination of the elementary graphs. The authors use the power rate function to investigate the tradeoff between energy efficiency and throughput. They give lower and upper bounds on the power rate function. They exploit the geometric structure of the interference model and give a

[1] In Figure 5.2, if A is transmitting to B, another transmitter D is the hidden terminal to A and there is collision at B. The free of secondary interference model prevents such hidden terminal problems.

sufficient condition for schedulability of a routing. After solving the linear program, they use greedy coloring to obtain tighter results.

Kumar et al. [31] give an LP formulation with an approximation factor of 5 for the problem of maximizing the throughput considering both scheduling and routing. They also introduce a congestion aware path selection heuristic.

The set of constraints derived from either Kodialam and Nandagopal [30], Jain et al. [26], Wu et al. [66], Kumar et al. [31] or any new improvement can be represented by (5.11):

$$\text{Constraints for schedulability of a flow, e.g., (5.9) with } \beta = 2/3 \text{ or (5.10).} \qquad (5.11)$$

Linearity is a convenient feature of the schedulability constraints. As a result, the schedulability constraints can be added to LP (5.6) to calculate a maximum lifetime of a wireless network. It works in a plug-and-play way.

5.5 Lossy Links

Most previous work on energy efficiency based on an LP model, e.g., [14, 33, 56, 57] implicitly assumes the wireless links are lossless. Loss may be ignored in wireline networks when formulating an LP network flow model, because loss is negligible. This may not be reasonable in wireless networks. A wireless link is usually lossy and some applications need reliable transmission. First, simple examples are given to illustrate the impact of lossy links.

5.5.1 Illustrative Examples

Suppose the network operates on a single channel. Consider the free of secondary interference model, where a node can transmit to or receive from at most one node in each time slot.

The first example will show that lossy links may affect both the maximum achievable throughput and the routing. This example is the same as that in Figure 5.2, except that in Figure 5.3, link BC is lossy and only 25% of transmissions are successful (i.e. a loss rate of 75%). In this case, path $ABCD$ can only achieve a throughput of $15/6 = 2.5Mbps$. Path ABD is preferable now, which can achieve a throughput of $3.75Mbps$. Because edges (B, C), (C, D) and (B, D) can't be active at the same time, routing on both paths $ABCD$ and ABD won't increase the throughput.

The second example will show the impact of lossy links on energy efficiency and routing. On the topology in Figure 5.4, $3Mbps$ data are to be transmitted from A to D. Every link has $10Mbps$ bandwidth. Nodes B, C, E have initial energy of $10J$, $10J$ and $2J$, respectively, and nodes A and D have infinite amount of energy. Suppose one unit of transmission, reception and overhearing at nodes B, C and E consumes one unit of energy. First assume links are lossless. Edges in $\{(A, B), (C, D)\}$ or in $\{(A, C), (B, D)\}$ can be active simultaneously.

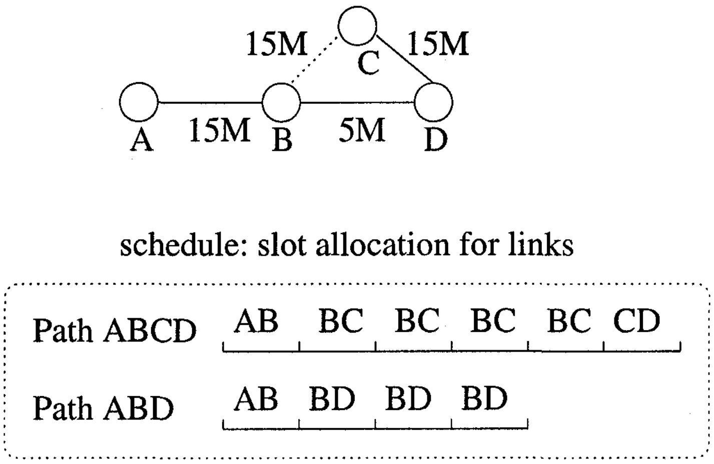


Figure 5.3: The topology and the transmission schedules, link BC is lossy

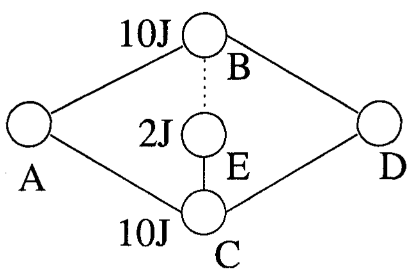


Figure 5.4: Lifetime without or with lossy links

Because of the overhearing at node E from both B and C, any routing of $3Mbps$ on paths ABD and ACD achieves the minimax energy utilization, resulting in a lifetime[2] of $\frac{2}{3}$. Now suppose edge (B, E) has 100% loss rate and the other edges are lossless. An optimal routing to minimax energy utilization (thus to maximize lifetime) is to assign $2Mbps$ to path ABD and $1Mbps$ to ACD. This yields a lifetime of 2, which is longer than $\frac{2}{3}$. The lifetime can be longer in a lossy network, where some broadcast packets are lost. Longer lifetimes are also achieved in several cases in the experiments as will be shown in Section 6.5.

5.5.2 Network Flow with Lossy Links

Due to links being lossy, a packet may require several transmissions. Thus modifications need to be made to the usual flow conservation constraints. Assume there is a *link loss factor* $\gamma_{ij} \geq 1$ for each edge (i, j), which measures the average number of transmissions needed to successfully transmit a packet on the link. It characterizes the quality of the transmission channel. The loss may result from multi-path fading, attenuation, etc. As-

[2]The definition of lifetime as until the first node dies is used. Its validity, as shown in this example where a node not on a transmission path dies first, is an interesting question. Redefinition of lifetime is worth further investigation.

sume a synchronized time slotted system in an interference-limited environment. With a scheduling scheme, there may be no interference and thus interference is not a factor for the loss. Assume a loss happens in the transmission medium. That is, after the sender transmits a packet, it may or may not get lost. Thus, if the packet is lost, the receiver and the neighboring nodes can not hear it at all. If there is a *constant* link loss factor γ_{ij} for each edge (i, j), we have linear flow conservation constraints. The routing definition (2.4) remains the same. The definition of flow $\mathbf{g}$ in (2.5) becomes:

$$\begin{cases} \forall \text{ pairs } i \rightarrow j: \sum_{(i,u)\in out(i)} \frac{g_{ij}(i,u)}{\gamma_{iu}} - \sum_{(v,i)\in in(i)} \frac{g_{ij}(v,i)}{\gamma_{vi}} = d_{ij} \\ \forall \text{ pairs } i \rightarrow j, \text{ nodes } k \neq i \neq j: \sum_{(k,u)\in out(k)} \frac{g_{ij}(k,u)}{\gamma_{ku}} - \sum_{(v,k)\in in(k)} \frac{g_{ij}(v,k)}{\gamma_{vk}} = 0 \\ \forall \text{ pairs } i \rightarrow j, \forall \text{ edges } (u,v): g_{ij}(u,v) \geq 0 \\ \forall \text{ pairs } i \rightarrow j: d_{ij} \geq 0 \end{cases} \tag{5.12}$$

In (5.12), $g_{ij}(u, v)$ denotes the expected flow of OD pair $i \rightarrow j$ on edge (u, v), due to retransmissions; while $\frac{g_{ij}(u,v)}{\gamma_{uv}}$ denotes the effective flow that is equal to the amount of data to be transmitted. We have $g_{ij}(s, t) = \gamma_{st} d_{ij} f_{ij}(s, t)$.

5.5.3 Energy Consumption with Lossy Links

The energy consumption model needs to change in a lossy environment. Since $g_{ij}(u, v)$ denotes the expected flow originating for OD pair $i \rightarrow j$ on edge (u, v), there is no change for the term for transmission. For reception, node s receives one copy out of γ_{ts} transmissions from t to s. For overhearing, node s receives one copy out of γ_{ts} transmissions from t to k. Thus, with lossy links, the energy consumption of node s for d_{ij} is,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{(s,t)\in out(s)} g_{ij}(s,t) tx(s,t) \\ & + \sum_{(t,s)\in in(s)} \frac{g_{ij}(t,s)}{\gamma_{ts}} r(s) \\ & + \sum_{(t,s)\in in(s)} \sum_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} \frac{g_{ij}(t,k)}{\gamma_{ts}} h(s) \end{aligned} \tag{5.13}$$

Or, equivalently,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{(s,t)\in out(s)} \gamma_{st} d_{ij} f_{ij}(s,t) tx(s,t) \\ & + \sum_{(t,s)\in in(s)} d_{ij} f_{ij}(t,s) r(s) \\ & + \sum_{(t,s)\in in(s)} \sum_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} \frac{\gamma_{tk} d_{ij} f_{ij}(t,k)}{\gamma_{ts}} h(s) \end{aligned} \tag{5.14}$$

When a wireless link is lossless, its loss factor γ is 1.

5.5.4 Maximum Lifetime with Lossy Links

The LP formulation to compute the maximum lifetime will be presented. The flow conservation constraints with lossy links follow:

$$\begin{cases} \forall \text{ pairs } i \to j: \sum\limits_{(i,t)\in out(i)} \frac{g_{ij}(i,t)}{\gamma_{it}} = d_{ij} \\ \forall \text{ pairs } i \to j, k \neq i,j: \sum\limits_{(k,u)\in out(k)} \frac{g_{ij}(k,u)}{\gamma_{ku}} - \sum\limits_{(v,k)\in in(k)} \frac{g_{ij}(v,k)}{\gamma_{vk}} = 0 \end{cases} \tag{5.15}$$

For a given traffic matrix, the following LP gives an optimal routing that minimizes the maximum energy utilization, with variables η and flow $\mathbf{g}$.:

$$\begin{array}{l} \min\limits_{\eta,g} \eta \\ \forall \text{nodes } s: \sum\limits_{i,j} \text{energy}_s(i,j)/pow_0(s) \leq \eta \\ \text{Constraints (2.5), (2.6), (2.7), (5.11) and (5.15).} \end{array} \tag{5.16}$$

5.6 Summary

This chapter presents the energy consumption model, the definitions of energy utilization, maximum energy utilization and minimax (optimal) energy utilization, competitive analysis framework, formulations for lossy links, and linear expressions for schedulability constraints. This chapter provides the background for the next chapter, where LP formulations for traffic-oblivious energy-aware routing will be presented and their performance will be evaluated.

Chapter 6

Traffic-Oblivious Energy-Aware Routing For Multihop Wireless Networks

In this chapter, LP formulations for traffic-oblivious energy-aware routing will be presented and their performance will be evaluated. Chapter 5 provided the background materials.

6.1 Introduction

The traffic demand may not be known a priori in many scenarios, e.g. wireless community mesh networks or base stations connected by wireless links. It is desirable to allow for errors, deviation and uncertainties in traffic prediction when designing a routing scheme. Two approaches may achieve this, namely, adaptive and oblivious.

A routing scheme may be adaptive to the traffic demand and the network conditions such as the remaining energy level in an energy-constrained case. Some adaptive approaches can bound the performance, e.g. [28, 33, 39]. They need to periodically collect information such as the current energy level. Collecting network information causes extra energy consumption. An alternative approach is to investigate the feasibility and performance of a routing scheme oblivious to the traffic demand and network information.

The problem of designing energy-efficient routing for multihop wireless networks with changing and uncertain traffic demands is investigated. Polynomial size LP models are developed to design such a routing scheme. The routing is fixed[1], thus it is oblivious to changes and uncertainties of the traffic. It is also oblivious to the current state of the network, such as the current energy level of wireless nodes and the current network load. It does not need to collect network information except for the stationary topology and the initial energy level. The routing achieves minimax energy utilization. Thus it is energy-

[1]The routing is "fixed" in the sense that there is a single output of the LP model. It can be implemented in an opportunistic way as discussed in Section 6.7.

aware. The routing scheme considers interference and loss. It achieves energy efficiency nearly optimally as shown in the experimental results. The adaptive approaches in [28, 39] give logarithmic performance guarantee. In contrast, for a given topology, the LP models give low performance guarantee (a low oblivious ratio) in the studied cases. Furthermore, an oblivious approach saves the energy consumption for network information collection used by an adaptive approach.

The traffic-oblivious energy-aware routing is investigated in our published paper [38], mainly in an interference-free and lossless environment. The extensions to consider interference and loss in LP formulations are based on our technical report [37].

6.2 Overview

In the next sections, LPs will be developed for the traffic-oblivious energy-aware routing, and their performance will be evaluated. It starts with the case in which there is no interference and links are lossless. When interference is not present, the routing can work well without considering scheduling. First, in Section 6.3, the case of a single sink with all other nodes as sources is studied. A potential application is a wireless sensor network in which every sensor reports to a single node, where there are unknown, unexpected or unscheduled events so that it is difficult to accurately predict the traffic demand. Then, in Section 6.4, the case where communication may happen between all pairs of nodes is studied. A potential application is wireless community mesh networks with energy constraints. Next, after studying the impact of lossy links on maximum lifetime of multihop wireless networks with given traffic demands in Section 6.5, the case in which interference is present and links are lossy is studied in Section 6.6. Additional linear constraints can be added to guarantee schedulability of a routing. Reliable transmission is also considered when links are lossy. Implementation issues are discussed in Section 6.7.

It is easy to adapt the LP models to the cases of multiple sources and/or multiple sinks, i.e., communication happens only between certain pair(s) of nodes. LPs are developed for the case where energy is a constraint and not renewable. The LP models can be generalized to other problems such as lifetime maximization when the energy is renewable and maximization of data extraction with energy constraints. The LP models are general enough for several radio transmission models, such as omni-directional and directional antennas and a radio equipped with various possible granularity of transmission power levels. They can also work with a multi-channel and/or multi-radio wireless system.

Table 6.1 shows the LPs to be presented for various scenarios. Details of derivation will be presented for LP (6.9) and LP (6.17). Among all the LPs, LP (6.9) is the least complicated and LP (6.17) is most complicated. As will be clear later, LPs for no knowledge of TM can be derived from LPs with approximate knowledge of TM.

		single-sink	all-pair
lossless, interference-free	no TM	LP (6.9)*	
	approximate TM	LP (6.10)	LP (6.11)
lossy, interference-limited	no TM		
	approximate TM	LP (6.12)	LP (6.17)*

Table 6.1: LPs to be presented for various scenarios. An asterisk means the full derivation of the LP will be given.

Before the details of derivation of LP formulations and the results of performance study are shown, the main theorem of this study is presented.

Theorem 1. *The optimal oblivious ratio with respect to energy efficiency and the optimal traffic-oblivious energy-aware routing of a multihop wireless network can be computed by a linear program with $O(n^3 + n^2m)$ variables and $O(n^3 + n^2m)$ constraints, where n and m are the numbers of nodes and edges in the graph representation of the network. This holds when linear constraints are added to guarantee the schedulability of routing when interference is present and reliable transmission when links are lossy.*

A multihop wireless network with a single sink is a special case. Its optimal oblivious ratio and optimal oblivious routing can be computed by a LP with $O(n^2 + nm)$ variables and $O(n^2 + nm)$ constraints.

Theorem 1 can be proved when developing the LP models, by counting the number of variables and constraints. For a multihop wireless network with a single sink, the n-fold reduction in the complexity is due to the n-fold reduction in the number of OD pairs, since there is a single destination.

6.2.1 Performance Study Setup

Performance studies will be conducted for the LP models developed later. The experimental setup is placed here since it is common to all the performance studies for the LP models for wireless networks developed in this chapter.

Random topologies are used for the performance studies. Nodes are put in a $k \times k$ grid. A cell represents a $10m \times 10m$ area. In each cell of the grid, a node is put at a random position. The initial energy level of each node is set randomly, uniformly within $[20J, 30J]$. Note the oblivious ratio is invariant with the scaling of the initial energy level. For simplicity, a disk model for radio transmission is used. That is, suppose the maximum transmission range of node u is R_{max}, there is an edge (u, v) if $R_{max} \geq dist(u, v)$, where $dist(u, v)$ denotes the distance between u and v. In the simulations, every node has the same maximum transmission range. Experiments on networks of various sizes are conducted. For each size of the network, two maximum transmission ranges, 15m and 20m, are studied.

The energy model in [25] is used to instantiate $tx(u, v)$, $r(u)$ and $h(u)$ in the energy consumption model discussed in Section 5.3.1 and Section 5.5.3 for lossy links. That is, $tx(u,v) = E_{elec} + \epsilon_{amp} \times dist^2(u,v)$ and $r(u) = E_{elec}$, where E_{elec} represents the energy consumption for running the transmitter or the receiver circuitry, ϵ_{amp} represents the energy consumption for running the transmitter amplifier to achieve an acceptable signal-noise ratio. Set $h(u) = r(u)$, i.e., assume that the overhearing consumes the same amount of energy per unit of message as the reception. As in [25], $E_{elec} = 50nJ/bit$ and $\epsilon_{amp} = 100pJ/bit/m^2$.

Note that the LP models developed later do not make the assumptions as in the experimental setup, e.g., the disk transmission model and the energy consumption model in [25] as discussed above. The LP models are more general. For example, as discussed in Section 5.3.1, the LP models can handle cases in which a node can vary its transmission range with various precisions, as well as the case of radio irregularity problem [65]. The LP models do not require a particular energy consumption model: they work well once $tx(u,v)$, $r(u)$ and $h(u)$ can be computed before forming the LPs.

6.3 Interference-free Lossless: A Single Sink Case

In this section, LP models are developed to compute the oblivious ratio for a multihop wireless network with a single sink, when there is no or approximate knowledge of the traffic demand. The sink node is assumed to have infinite energy capacity. First the detailed definitions of a routing **f** and the energy consumption $\mathbf{energy}_s$ are introduced. Note, the definitions of routing (2.4) and energy consumption (5.1) are for the case where transmission happens between all pairs of nodes.

When there is a single sink in a multihop wireless network, denoted as T, the destination of any OD pair is T. The traffic matrix is reduced to a traffic vector, with each entry d_i denoting the amount of traffic originating from node i. A routing $f_i(s,t)$ specifies what fraction of d_i is routed along edge (s,t). The traffic on edge (s,t) for d_i is $d_i f_i(s,t)$.

Routing **f** is defined as:

$$\begin{cases} \forall \text{ nodes } i \neq T: \sum_{(i,j)\in out(i)} f_i(i,j) - \sum_{(h,i)\in in(i)} f_i(h,i) = 1 \\ \forall \text{ nodes } i \neq T, \forall k \neq i, T: \\ \quad \sum_{(k,l)\in out(k)} f_i(k,l) - \sum_{(j,k)\in in(k)} f_i(j,k) = 0 \\ \forall i \neq T, \forall \text{ edges } (s,t): f_i(s,t) \geq 0 \end{cases} \tag{6.1}$$

The energy consumption of node s for d_i is,

$$\begin{aligned} \text{energy}_s(i) = & \sum_{(s,t)\in out(s)} d_i f_i(s,t) tx(s,t) \\ & + \sum_{(t,s)\in in(s)} d_i f_i(t,s) r(s) \\ & + \sum_{(t,s)\in in(s)} \sum_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} d_i f_i(t,k) h(s) \end{aligned} \tag{6.2}$$

The first term in $\text{energy}_s(i)$ is the energy consumption for transmission; the second for reception and the third for overhearing. $I_{(t,s)}^{(t,k)}$ is an indicator function as defined in (5.2). The total energy consumption of node s for all d_i's is,

$$\mathbf{energy}_s = \sum_i \text{energy}_s(i) \tag{6.3}$$

Since $d_T = 0$, in (6.3) and later formulations for the single-sink case, the sum is taken over i rather than $i \neq T$ for brevity.

6.3.1 Routing With No Knowledge of Traffic

Similar to Azar et al. [10], the optimal oblivious routing of a multihop wireless network can be obtained by solving an LP with a polynomial number of variables, but infinitely many constraints. This LP is called "master LP":

$$\begin{aligned}
&\min_{r,f,d} r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \text{ nodes } s \neq T, \forall \text{ TMs } \mathbf{tm} \text{ with OPTE}(\mathbf{tm}) = 1: \\
&\quad \sum_i \text{energy}_s(i)/pow_0(s) \leq r
\end{aligned} \tag{6.4}$$

The oblivious ratio is invariant with the scaling of the traffic matrices or the scaling of the initial energy level. Thus, when calculating the oblivious ratio, it is sufficient to consider traffic matrices with OPTE($\mathbf{tm}$) = 1. Another benefit of using traffic matrices with OPTE($\mathbf{tm}$) = 1 is that the objective of the LP r, which is the maximum energy utilization of the oblivious routing, is just the oblivious ratio of the network.

Given a routing $\mathbf{f}$, the constraint of the master LP (6.4) can be checked by solving the following slave LP for each node $s \neq T$ to examine whether the objective is upper bounded by r or not.

$$\begin{aligned}
&\max_{g,d} \sum_i \text{energy}_s(i)/pow_0(s) \\
&g_i(u,v) \text{ is a flow of demand } d_i \\
&\forall \text{ nodes } u \neq T: \\
&\quad \sum_i \sum_{(u,v)\in out(u)} g_i(u,v)tx(u,v) \\
&\quad + \sum_i \sum_{(v,u)\in in(u)} g_i(v,u)r(u) \\
&\quad + \sum_i \sum_{(v,u)\in in(u)} \sum_{(v,w)\in out(v,-u)} I_{(v,u)}^{(v,w)} g_i(v,w)h(u) \\
&\quad \leq pow_0(u) \\
&\forall \text{ nodes } i \neq T: d_i \geq 0
\end{aligned} \tag{6.5}$$

The constraints of LP (6.5) guarantee that the traffic can be routed with maximum energy utilization of 1. That is, the constraint "$\forall$ nodes $s \neq T, \forall$ TMs $\mathbf{tm}$ with OPTE($\mathbf{tm}$) = 1" in LP (6.4) is equivalent with the constraints of LP (6.5). In the energy consumption constraint of LP (6.5), the first term on the left hand side is the energy consumption for transmission; the second for reception and the third for overhearing.

Flow **g** in slave LP (6.5) is defined as,

$$\begin{cases} \forall \text{ nodes } k \neq T, \forall i \neq k \text{ and } i \neq T: \\ \quad \sum\limits_{(k,u)\in out(k)} g_i(k,u) - \sum\limits_{(v,k)\in in(k)} g_i(v,k) = 0 \\ \forall \text{ nodes } i \neq T: \quad \sum\limits_{(i,u)\in out(i)} g_i(i,u) - d_i = 0 \\ \forall \text{ edges } (u,v), u \neq T, \forall i \neq T: g_i(u,v) \geq 0 \\ \forall \text{ nodes } i \neq T: d_i \geq 0 \end{cases} \tag{6.6}$$

Although the above "master-slave" LPs can solve the optimal oblivious routing problem in polynomial time based on the Ellipsoid algorithm [8, 10, 49], it is not practical for large networks [8]. Inspired by the work of Applegate and Cohen [8], simpler LP models are derived to compute the oblivious ratio.

The formulation can be simplified by collapsing flows g_i on an edge $u \to v$, i.e., using $g(u,v) = \sum\limits_i g_i(u,v)$. As well, by relaxing the flow conservation constraint from equality to ≤ 0, node i is allowed to deliver more flow than demanded, which does not affect the maximum energy utilization of 1. The slave LP for node $s \neq T$ is thus:

$$\begin{array}{l} \max\limits_{g,d} \frac{1}{pow_0(s)}\{\sum\limits_i \sum\limits_{(s,t)\in out(s)} d_i f_i(s,t) tx(s,t) \\ \qquad + \sum\limits_i \sum\limits_{(t,s)\in in(s)} d_i f_i(t,s) r(s) \\ \qquad + \sum\limits_i \sum\limits_{(t,s)\in in(s)} \sum\limits_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} d_i f_i(t,k) h(s)\} \\ \forall \text{ nodes } i \neq T: \\ \quad \sum\limits_{(v,i)\in in(i)} g(v,i) - \sum\limits_{(i,u)\in out(i)} g(i,u) + d_i \leq 0 \\ \forall \text{ nodes } u \neq T: \\ \quad \sum\limits_{(u,v)\in out(u)} g(u,v) tx(u,v) \\ \quad + \sum\limits_{(v,u)\in in(u)} g(v,u) r(u) \\ \quad + \sum\limits_{(v,u)\in in(u)} \sum\limits_{w\in out(v,-u)} I_{(v,u)}^{(v,w)} g(v,w) h(u) \\ \quad \leq pow_0(u) \\ \forall \text{ edges } (u,v), u \neq T: g(u,v) \geq 0 \\ \forall \text{ nodes } i \neq T: d_i \geq 0 \end{array} \tag{6.7}$$

The dual of the simplified slave LP (6.7) (for node $s \neq T$) is:

$$\begin{array}{l} \min\limits_{\pi,p} \sum\limits_{u\neq T} \pi_s(u) pow_0(u) \\ \forall \text{ nodes } i \neq T: \\ \quad p_s(i) \geq \frac{1}{pow_0(s)}\{ \sum\limits_{(s,t)\in out(s)} f_i(s,t) tx(s,t) \\ \qquad + \sum\limits_{(t,s)\in in(s)} f_i(t,s) r(s) \\ \qquad + \sum\limits_{(t,s)\in in(s)} \sum\limits_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} f_i(t,k) h(s)\} \\ \forall \text{ edges } (u,v), u \neq T: \\ \quad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\ \quad + \sum\limits_{(u,k)\in out(u,-v)} I_{(u,k)}^{(u,v)} h(k)\pi_s(k)\} - p_s(u) + p_s(v) \geq 0 \\ \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i) \geq 0 \\ p_s(T) = 0, \pi_s(T) = 0 \end{array} \tag{6.8}$$

The dual variable $p_s(i)$ corresponds to the flow conservation constraint for the demand d_i. Since there is no conservation constraint for the demand d_T, $p_s(T) = 0$ is introduced for convenience. The dual variable $\pi_s(u)$ corresponds to the capacity constraint for node u. Since there is no capacity constraint for node T, $\pi_s(T) = 0$ is introduced.

According to the LP duality theory [4], the primal LP and its dual LP have the same optimal values if they exist. That is, LP (6.7) and LP (6.8) are equivalent. Replacing the constraint in the master LP (6.4) with LP (6.8), a polynomial size LP (6.9) is obtained to compute the optimal oblivious ratio when there is a single sink. LP (6.9) has $O(n^2 + nm)$ variables and $O(n^2 + nm)$ constraints, where n and m are the numbers of nodes and edges.

$$
\begin{aligned}
&\min_{r,f,\pi,p} r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \text{ nodes } s \neq T: \\
&\quad \sum_{u \neq T} \pi_s(u) pow_0(u) \leq r \\
&\quad \forall \text{ nodes } i \neq T: \\
&\quad p_s(i) \geq \frac{1}{pow_0(s)} \{ \sum_{(s,t) \in out(s)} f_i(s,t) tx(s,t) \\
&\qquad\qquad + \sum_{(t,s) \in in(s)} f_i(t,s) r(s) \\
&\qquad\qquad + \sum_{(t,s) \in in(s)} \sum_{k \in out(t,-s)} I_{(t,s)}^{(t,k)} f_i(t,k) h(s) \} \\
&\quad \forall \text{ edges } (u,v), u \neq T: \\
&\quad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\
&\quad + \sum_{k \in out(u,-v)} \{ I_{(u,k)}^{(u,v)} h(k) \pi_s(k) \} - p_s(u) + p_s(v) \geq 0 \\
&\quad \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i) \geq 0 \\
&\quad p_s(T) = 0, \pi_s(T) = 0
\end{aligned}
\tag{6.9}
$$

6.3.2 Routing with Approximate Knowledge of Traffic

LP (6.10) is given directly to compute the optimal oblivious routing[2] for a multihop wireless network with a single sink when approximate knowledge of traffic demand is bounded, i.e., the traffic demand d_i is in the range of $[a_i, b_i]$ $(0 \leq a_i \leq b_i)$. Its derivation is similar to that for LP (6.9), except there are new constraints for the approximate knowledge of traffic demand in the range, $a_i \leq d_i \leq b_i$. The range constraints are added to the slave LP. When its dual is formulated, dual variables $w_s^+(i)$ and $w_s^-(i)$ are introduced for the range constraints. See the derivation for LP (6.17) for the handling of the range constraints. LP (6.10) has $O(n^2 + nm)$ variables and $O(n^2 + nm)$ constraints.

[2]With a slight misuse of terms, the routing that minimizes the competitive ratio over the range restriction on the traffic matrix is also called the "optimal oblivious routing", and its competitive ratio the "optimal oblivious ratio".

$$
\begin{array}{l}
\min\limits_{r,f,\pi,p,w^+,w^-} \quad r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s \neq T: \\
\quad \sum\limits_{u \neq T} \pi_s(u) pow_0(u) \leq r \\
\quad \forall \text{ nodes } i \neq T: \\
\quad\quad p_s(i) + w_s^+(i) - w_s^-(i) \geq \\
\quad\quad\quad \frac{1}{pow_0(s)} \{ \sum\limits_{(s,t) \in out(s)} f_i(s,t) tx(s,t) \\
\quad\quad\quad\quad + \sum\limits_{(t,s) \in in(s)} f_i(t,s) r(s) \\
\quad\quad\quad\quad + \sum\limits_{(t,s) \in in(s)} \sum\limits_{(t,k) \in out(t,-s)} I_{(t,s)}^{(t,k)} f_i(t,k) h(s) \} \\
\quad \forall \text{ edges } (u,v), u \neq T: \\
\quad\quad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\
\quad\quad + \sum\limits_{(u,k) \in out(u,-v)} I_{(u,k)}^{(u,v)} h(k) \pi_s(k) - p_s(u) + p_s(v) \geq 0 \\
\quad \sum\limits_{i} \{ w_s^-(i) a_i - w_s^+(i) b_i \} \geq 0 \\
\quad \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i), w_s^+(i), w_s^-(i) \geq 0 \\
\quad p_s(T) = 0, \pi_s(T) = 0
\end{array}
\tag{6.10}
$$

6.3.3 Performance Study

Experiments are set up as discussed in Section 6.2.1. Experiments are conducted on networks of sizes 25, 36, 49, 81, 100 and 121. The sink is either in the center or in the corner cell.

The oblivious ratio of a multihop wireless network is computed by LP (6.9). The oblivious ratios of the studied networks are shown in the last column under ∞ (which means we have no knowledge of traffic demands, as will be clear later in this section) in Table 6.2 for the case the sink is in the center, and in Table 6.3 for the case the sink is in the corner. The results are excellent, considering the oblivious ratios are achieved without any knowledge of traffic demands, and only an oracle can achieve the ratio of 1.

There may be approximate estimation of the traffic demand in a multihop wireless network. It is expected that with some knowledge of traffic demands, lower competitive ratios can be achieved. In the following the performance of LP (6.10) is studied, if there is knowledge of the degree of accuracy of the traffic estimation, for a topology, a traffic matrix **tm** and an "error margin" $w > 1$. The oblivious ratio of a network will be studied, given the knowledge that the traffic demand is in the range of $[d_i/w, wd_i]$ with respect to the base traffic matrix d_i's. First, the d_i's need to be decided.

Four traffic models are used to determine the base traffic matrix **tm**: Gravity, Bimodal, Random and Uniform, to attempt to capture some broad classes of traffic demands in multihop wireless networks. They are denoted as G, B, R and U respectively in the tables. In the Gravity model, the amount of traffic originating from node i, d_i, is proportional to $pow_0(i)$, the initial energy level of node i. In the Bimodal, a small portion of nodes have a large amount of traffic, while a large number of nodes have small amount of traffic.

N	R_{max}	TM	1.5	2.0	3.0	∞
49	15m	U	1.2264	1.3892	1.5808	1.8239
		G	1.2256	1.3879	1.5810	
		B	1.2612	1.4430	1.5831	
		R	1.2177	1.3773	1.5815	
	20m	U	1.2852	1.4884	1.7138	1.9651
		G	1.2846	1.4875	1.7163	
		B	1.3018	1.5169	1.6943	
		R	1.2954	1.4955	1.6772	
81	15m	U	1.1441	1.2725	1.5154	1.9964
		G	1.1439	1.2727	1.5169	
		B	1.1406	1.2824	1.4966	
		R	1.1377	1.2681	1.5208	
	20m	U	1.1605	1.3086	1.5650	2.0242
		G	1.1600	1.3080	1.5663	
		B	1.1883	1.3493	1.5819	
		R	1.1576	1.3037	1.5544	
100	15m	U	1.0673	1.1442	1.3221	1.9065
		G	1.0669	1.1429	1.3195	
		B	1.0887	1.1851	1.3901	
		R	1.0556	1.1273	1.3037	
	20m	U	1.0920	1.1834	1.3761	1.9752
		G	1.0918	1.1825	1.3743	
		B	1.1219	1.2360	1.4676	
		R	1.0995	1.1923	1.3872	
121	15m	U	1.0604	1.1268	1.3012	1.9071
		G	1.0609	1.1268	1.3007	
		B	1.0780	1.1529	1.3373	
		R	1.0573	1.1305	1.3166	
	20m	U	1.0883	1.1886	1.4129	2.0751
		G	1.0875	1.1874	1.4113	
		B	1.0784	1.2016	1.4803	
		R	1.0960	1.2007	1.4263	

Table 6.2: Oblivious ratios: single sink in the center

N	R_{max}	TM	1.5	2.0	3.0	∞
49	15m	U	1.000+	1.000+	1.000+	1.000+
		G	1.000+	1.000+	1.000+	
		B	1.000+	1.000+	1.000+	
		R	1.000+	1.000+	1.000+	
	20m	U	1.0359	1.0696	1.1473	1.4758
		G	1.0346	1.0680	1.1441	
		B	1.0470	1.0850	1.1296	
		R	1.0347	1.0601	1.1138	
81	15m	U	1.0057	1.0114	1.0278	1.1838
		G	1.0055	1.0109	1.0267	
		B	1.0082	1.0149	1.0318	
		R	1.0012	1.0023	1.0056	
	20m	U	1.0044	1.0090	1.0224	1.1872
		G	1.0042	1.0087	1.0214	
		B	1.0012	1.0026	1.0067	
		R	1.0051	1.0104	1.0230	
100	15m	U	1.0253	1.0477	1.0969	1.3074
		G	1.0250	1.0471	1.0964	
		B	1.0348	1.0564	1.0949	
		R	1.0084	1.0158	1.0348	
	20m	U	1.0073	1.0173	1.0446	1.2723
		G	1.0069	1.0163	1.0421	
		B	1.0036	1.0085	1.0203	
		R	1.0080	1.0164	1.0378	
121	15m	U	1.0121	1.0263	1.0622	1.4795
		G	1.0118	1.0256	1.0606	
		B	1.0284	1.0566	1.1194	
		R	1.0041	1.0091	1.0227	
	20m	U	1.0141	1.0296	1.0692	1.4782
		G	1.0140	1.0294	1.0683	
		B	1.0097	1.0181	1.0441	
		R	1.0080	1.0152	1.0324	

Table 6.3: Oblivious ratios: single sink in the corner

In the study, 80% of the nodes have traffic demands determined by a normal distribution $N(1.0, 0.1)$; while traffic demands of 20% of the nodes are determined by $N(10.0, 1.0)$. $N(\mu, \sigma^2)$ denotes a normal distribution with mean μ and variance σ^2. In the Random model, d_i is chosen at random from a uniform distribution on the range $[1, 100]$. In a Uniform model, all the nodes have the same amount of traffic. The Gravity and the Bimodal traffic models are inspired by the study on the Internet traffic estimation in [70] and [13] respectively, which may reflect the technical expectation to and the social phenomenon of a network (the Internet). In a wireless network, a node with high energy capacity may tend to transmit more data. It is possible that, in some applications, some "hotspot" areas may have much more data to transmit.

Tables 6.2 shows the results for the sink in the center with the error margin w of 1.5, 2.0 and 3.0, for the four base traffic models respectively. For each network size N, each maximum transmission range R_{max}, the oblivious ratios for the four base traffic models are on the same topology. LP (6.10) can achieve fairly low oblivious ratios with large error margins. Note that, with 50% error in traffic estimation, the performance is close to the optimal (the oblivious ratio is close to 1.0). As shown in Tables 6.3, when the sink is in the corner, the oblivious ratio can be much lower. The results of 1.000+ represent those slightly greater than 1.0.

Experiments are also conducted with 9 seeds for the random number generator, which may change the locations of the nodes (thus the graph), the initial energy level. Table 6.4 shows the min and max of the oblivious ratios over 9 seeds for Uniform model for the case the sink is in the corner.

N	R_{max}		1.5	2.0	3.0	∞
49	15m	min	1.000+	1.000+	1.000+	1.000+
		max	1.2329	1.3946	1.6091	1.9340
	20m	min	1.0100	1.0203	1.0438	1.1800
		max	1.3771	1.5880	1.7750	1.9767
81	15m	min	1.000+	1.000+	1.000+	1.0353
		max	1.0945	1.2125	1.4442	1.9652
	20m	min	1.0044	1.0090	1.0224	1.1872
		max	1.1706	1.3402	1.6354	2.0770
100	15m	min	1.0125	1.0293	1.0719	1.6205
		max	1.1166	1.2443	1.4811	2.0439
	20m	min	1.0734	1.1554	1.3527	1.9905
		max	1.1687	1.3078	1.5564	2.1073
121	15m	min	1.0275	1.0606	1.1444	1.8342
		max	1.0700	1.1387	1.3091	2.0263
	20m	min	1.0551	1.1000	1.1000	1.9874
		max	1.1028	1.2041	1.4209	2.1039

Table 6.4: Min and max oblivious ratios over 9 runs a single sink in the corner (Uniform base TM)

The energy consumption for reception and overhearing may be insignificant in some cases such as long-range transmission. Attempts are made to study how the LP models perform under such circumstances. A $k \times k$ grid is still used. However, each cell of the grid represents a $50m \times 50m$ area. Two maximum transmission ranges, 75m and 100m, are studied. Recall $tx(u,v) = E_{elec} + \epsilon_{amp} \times dist^2(u,v)$ and $r(u) = h(u) = E_{elec}$. Thus the distance plays an important role in energy consumption. It seems that the LP models perform similarly over the four base traffic models. In this set of experiments, the Gravity model and Random model are used to determine the base traffic matrix when there is approximate knowledge of the traffic demand. Experimental results in Table 6.5 and Table 6.6 show that when the energy consumption for reception and overhearing is less significant, the LP models can still achieve low oblivious ratios, especially when approximate knowledge of traffic is available.

N	R_{max}	TM	1.5	2.0	3.0	∞
49	75m	G	1.2985	1.4891	1.7232	2.1356
		R	1.3110	1.5294	1.7328	
	100m	G	1.3128	1.5465	1.8378	2.2395
		R	1.3405	1.5877	1.8332	
81	75m	G	1.1102	1.2111	1.4423	2.1934
		R	1.0987	1.1957	1.4251	
	100m	G	1.1580	1.3206	1.6335	2.2678
		R	1.1615	1.3331	1.6350	
100	75m	G	1.0419	1.0886	1.1973	1.9786
		R	1.0427	1.0840	1.2036	
	100m	G	1.0720	1.1539	1.3308	2.1054
		R	1.0659	1.1404	1.3253	
121	75m	G	1.0372	1.0713	1.1648	1.9499
		R	1.0317	1.0605	1.1899	
	100m	G	1.0764	1.1545	1.3463	2.3008
		R	1.0572	1.1310	1.3324	

Table 6.5: Oblivious ratios: a single sink in the center, transmission dominates energy consumption

6.4 Interference-free Lossless: All Pair Case

The multihop wireless network with a single sink is a special case of communication over multihop wireless networks, where there may be traffic between all pairs of nodes. When all pairs of nodes may have traffic, an entry d_{ij} in a traffic matrix denotes the amount of traffic of OD pair $i \rightarrow j$. Usually no node is assumed to have infinite energy capacity. For the all-pair case, the definition of routing is (2.4) and the energy consumption model is (5.1).

N	R_{max}	TM	1.5	2.0	3.0	∞
49	75m	G	1.000+	1.000+	1.000+	1.000+
		R	1.000+	1.000+	1.000+	
	100m	G	1.0351	1.0676	1.1320	1.5637
		R	1.0301	1.0488	1.0934	
81	75m	G	1.0167	1.0379	1.0847	1.5360
		R	1.0031	1.0060	1.0135	
	100m	G	1.0208	1.0450	1.0972	1.6008
		R	1.0191	1.0359	1.0765	
100	75m	G	1.0169	1.0394	1.0884	1.6119
		R	1.0031	1.0064	1.0150	
	100m	G	1.0175	1.0404	1.0905	1.6119
		R	1.0152	1.0292	1.0639	
121	75m	G	1.0143	1.0265	1.0543	1.6078
		R	1.0054	1.0094	1.0199	
	100m	G	1.0181	1.0342	1.0691	1.6201
		R	1.0101	1.0174	1.0354	

Table 6.6: Oblivious ratios: a single sink in the corner, transmission dominates energy consumption

6.4.1 Routing Without Accurate Knowledge of Traffic

Similar techniques to those in Section 6.3.1 for derivation of LP models can be used here, e.g. flows g_{ij} on an edge $u \to v$ with the same origin can be collapsed with $g_i(u,v) = \sum_j g_{ij}(u,v)$ to simplify the LP formulation. LP (6.11) is directly given, which computes the optimal oblivious ratio for a multihop wireless network, when there is approximate knowledge of the traffic demand that d_{ij} is within the range of $[a_{ij}, b_{ij}]$.

$$
\begin{aligned}
&\min_{r,f,\pi,p,w^+,w^-} \quad r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \text{ nodes } s: \\
&\quad \sum_u \pi_s(u) pow_0(u) \le r \\
&\quad \forall \text{ nodes } i, j \neq i: \\
&\qquad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \ge \\
&\qquad \tfrac{1}{pow_0(s)} \{ \sum_{(s,t)\in out(s)} f_{ij}(s,t) tx(s,t) \\
&\qquad\qquad + \sum_{(t,s)\in in(s)} f_{ij}(t,s) r(s) \\
&\qquad\qquad + \sum_{(t,s)\in in(s)} \sum_{(t,k)\in out(t,-s)} I_{(t,s)}^{(t,k)} f_{ij}(t,k) h(s) \} \\
&\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \\
&\qquad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\
&\qquad + \sum_{(u,k)\in out(u,-v)} I_{(u,k)}^{(u,v)} h(k) \pi_s(k) \\
&\qquad - p_s(u,i) + p_s(v,i) \ge 0 \\
&\quad \sum_i \{ w_s^-(i,j) a_{ij} - w_s^+(i,j) b_{ij} \} \ge 0 \\
&\quad \forall \text{ nodes } u: \pi_s(u) \ge 0 \\
&\quad \forall \text{ nodes } i, j \neq i: p_s(i,j), w_s^+(i,j), w_s^-(i,j) \ge 0 \\
&\quad \forall \text{ nodes } i: p_s(i,i) = 0
\end{aligned}
\tag{6.11}
$$

When there is no knowledge of the traffic demand, i.e., the range is $[0, +\infty]$, the LP to compute the oblivious ratio can be obtained by removing the constraints, $\sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \geq 0$, and the variables $w_s^+(i,j)$ and $w_s^-(i,j)$ representing the range restrictions.

6.4.2 Performance Study: All Pair Case

Experiments are set up as discussed in Section 6.2.1. Topologies of sizes 25 and 36 are studied. The oblivious ratios of the studied networks are shown in the last column in Table 6.7 (denoted by the error margin ∞). These results are very good, since they are achieved without any knowledge of the traffic demand and without the ongoing network information collection.

Experiments are also conducted for the case approximate knowledge of traffic demands is available. Similar to Section 6.3.3, four traffic models are used to determine the base TM **tm**, when there is approximate knowledge of the traffic demand. In the Gravity model, the amount of traffic of the OD pair d_{ij} is proportional to $pow_0(i) \times pow_0(j)$. In the Bimodal, 20% of the pairs have traffic demand determined by $N(10.0, 1.0)$, while 80% of the pairs determined by $N(1.0, 0.1)$. A uniform distribution on $[1, 100]$ is used for the Random model. In the Uniform model, all OD pairs have the same amount of traffic.

With rough knowledge of the traffic demand, the competitive ratios can be much lower than that without any knowledge of traffic. With error margin $w = 1.5$, an oblivious routing that is at most $33.5\% - 46.5\%$ worse than the oracle optimal routing can be achieved. The results are very good on the studied topologies.

N	R_{max}	TM	1.5	2.0	3.0	∞
25	15m	U	1.3351	1.4928	1.6532	2.1671
		G	1.3346	1.4924	1.6532	
		B	1.3357	1.4925	1.6516	
		R	1.3318	1.4882	1.6448	
	20m	U	1.3732	1.5451	1.7113	2.2237
		G	1.3730	1.5449	1.7110	
		B	1.3575	1.5306	1.7030	
		R	1.3713	1.5418	1.7086	
36	15m	U	1.4287	1.6151	1.8094	2.4054
		G	1.4288	1.6151	1.8097	
		B	1.4277	1.6143	1.8019	
		R	1.4237	1.6134	1.8085	
	20m	U	1.4642	1.6826	1.8866	2.4397
		G	1.4646	1.6830	1.8870	
		B	1.4575	1.6819	1.8827	
		R	1.4648	1.6831	1.8866	

Table 6.7: Oblivious ratios: all pair case

Experiments are also conducted in the case that each cell of the grid represents a $50m \times 50m$ area to attempt to study how the LP models perform in multihop wireless networks when energy consumption for reception and overhearing is less significant. Two maximum transmission ranges, 75m and 100m, are used. The Gravity model and Random model are used when there is the range restriction on the base traffic matrix. Table 6.8 shows that the LP models can achieve low oblivious ratios (close to 1.0, the oracle optimal performance).

N	R_{max}	TM	1.5	2.0	3.0	∞
25	75m	G	1.4048	1.6377	1.8718	2.4018
		R	1.4054	1.6297	1.8647	
	100m	G	1.4868	1.7438	1.9655	2.4098
		R	1.4813	1.7342	1.9547	
36	75m	G	1.4253	1.6596	1.9346	2.6166
		R	1.4309	1.6652	1.9386	
	100m	G	1.5215	1.8107	2.1031	2.6479
		R	1.5230	1.8113	2.1039	

Table 6.8: Oblivious ratios: all pair case, transmission dominates energy consumption

6.5 Impact of Lossy Links on Performance of Multihop Wireless Network

Background materials for lossy links were presented in Section 5.5. Section 5.5.1 presented an example to show the impact of loss and Section 5.5.3 presented the energy consumption model with lossy links. Given accurate knowledge of traffic demands, the LP formulation to compute the maximum lifetime is presented in Section 5.5.4.

The impact of lossy links on the maximum lifetime is studied on random topologies. Experiments are set up as in Section 6.2.1. The loss ratio of each edge is uniformly set within $[0\%, 50\%]$. The capacity of each edge is set uniformly within $[10, 20]Mbps$. The traffic demand for an OD pair is set randomly, uniformly within $[1, 2]Mbps$. Note that all of the performance metrics discussed in this section are invariant with the scaling of link capacity and traffic demands. To consider interference, linear constraints (5.9) are used with $\beta = 1.0$.

Impact of loss on maximum lifetime. The maximum lifetime t, which is the inverse of the objective η of LP (5.16), is investigated when loss is considered or not. The energy consumption model with lossy links (5.13) is used. The measure $\frac{t_1}{t_0} \times 100\%$ is used to show the degree of the impact, where t_0 is the maximum lifetime when only interference is present in the network and links are lossless, while t_1 is the lifetime when both interference and loss are present. When a network is lossless, the link loss factor, γ, is 1.0 for each link in LP (5.16), including the energy consumption model (5.13). The energy model in [25] is used, as discussed in Section 6.2.1. The initial energy level of each node is set randomly, uniformly within $[20, 30]J$. Note that $\frac{t_1}{t_0}$ is invariant with the scaling of the initial energy level.

In Table 6.9, the minimum, median, mean and maximum of the impact measure for 9 runs of the experiments are reported. The mean of 9 runs has more than 86% of the maximum lifetime of the corresponding lossless networks. In most cases (except 3 out of 54), $\frac{t_1}{t_0}$ is greater than 0.75; while the mean loss ratio is 0.25. There are even cases where a lossy network has longer lifetime than the lossless counterpart. This might be counter-intuitive, since in a lossy environment, retransmissions are required thus energy is wasted. Taking a closer look at the broadcast nature of wireless communication, the results reveal that, due to loss, the saving in energy consumption for overhearing may compensate for the energy waste for retransmission. It is even possible to take advantage of the loss and design routings to improve energy efficiency, e.g. in the cases where $\frac{t_1}{t_0} > 1$ (there are 4 cases). LP (5.6) can compute such a routing.

N	R_{max}	min	median	mean	max
25	15m	76.841	90.891	93.024	114.089
25	20m	87.193	92.489	92.149	95.877
36	15m	83.552	89.047	93.396	118.050
36	20m	91.807	95.097	94.775	97.346
49	15m	67.519	88.493	86.719	94.825
49	20m	91.597	93.587	93.601	96.730

Table 6.9: Impact of loss on maximum lifetime (%)

The energy consumption model affects the impact of loss on the maximum lifetime. It is expected that with much lower energy consumption for overhearing, the gain due to the loss of broadcasting will be less significant. Thus, a close or longer lifetime as shown in Table 6.9 may not occur. The previous study shows that different network sizes have similar results. Here networks of size 25 are studied. The first and second rows in Table 6.10 for $h(u) = r(u)/10$ confirm the expectation. The extreme case is when overhearing does not consume energy. The third and fourth rows show the results.

N	R_{max}	$h(u)$	min	median	mean	max
25	15m	$r(u)/10$	59.173	79.277	77.187	86.101
25	20m	$r(u)/10$	77.482	82.381	82.661	85.651
25	15m	0	57.562	77.601	75.799	85.089
25	20m	0	76.673	81.225	80.872	84.013

Table 6.10: Impact of loss on maximum lifetime (%) when overhearing consumes different amounts of energy

Impact of overhearing on maximum lifetime with lossy links. The previous study considers the impact of overhearing on energy efficiency if overhearing is present. The following experiments study the impact of overhearing on the maximum lifetime, when overhearing is present in the network, but overhearing is or is not included in LP (5.16). When overhearing is not included, the term for overhearing in energy consumption model

(5.13) is removed. Both interference and loss are considered in the LP. The measure $\frac{t_1^o}{t_0^o} \times 100\%$ is used to show the degree of the impact, where t_0^o is the maximum lifetime when overhearing is not included in the LP, while t_1^o is the lifetime when overhearing is included. Networks of size 25 are studied. In Table 6.11, the minimum, median, mean and maximum of the impact measure for 9 runs of the experiments are reported. The first and third rows show the results when links have loss ratios uniformly in [0%, 50%]; while the second and fourth rows are for lossless networks. Overhearing has a huge impact on energy efficiency, especially for denser networks ($R_{max} = 20m$). On average, only 60% or much less (32%) lifetime can be achieved. The results suggest that, with omni-directional antennas, overhearing is an important factor to consider for energy efficiency.

N	R_{max}	loss ratio	min	median	mean	max
25	15m	$U[0, 0.5]$	49.628	58.757	59.347	76.011
25	15m	0	39.613	45.227	48.655	60.131
25	20m	$U[0, 0.5]$	32.817	35.325	36.548	45.063
25	20m	0	28.883	31.726	32.048	40.175

Table 6.11: Impact of overhearing on lifetime (%)

6.6 Interference-limited lossy-links case

In this section, concerns with interference and lossy links are discussed. In contrast to Section 6.5, there is no accurate knowledge of traffic demands. The techniques for deriving LP formulations are similar to those in Section 6.3, except that linear constraints for flow schedulability and reliable transmission are added.

6.6.1 A Single Sink Case

The LP for the single-sink case is given directly in LP (6.12). It calculates the oblivious routing with d_{ij} being within $[a_{ij}, b_{ij}]$. The LP to compute the oblivious routing with no knowledge of traffic demand can be obtained from LP (6.12).

$$
\begin{aligned}
&\min_{r,f,\pi,p,w^+,w^-} \quad r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \text{ nodes } s \neq T: \\
&\quad \sum_{u \neq T} \{\pi_s(u) pow_0(u) + \sum_v \kappa_s(u,v) c(u,v) + \beta \psi_s(u)\} \leq r \\
&\quad \forall \text{ nodes } i \neq T: \\
&\quad p_s(i) + w_s^+(i) - w_s^-(i) \geq \\
&\quad \frac{1}{pow_0(s)} \{ \sum_{(s,t) \in out(s)} \gamma_{st} f_i(s,t) tx(s,t) \\
&\qquad + \sum_{(t,s) \in in(s)} f_i(t,s) r(s) \\
&\qquad + \sum_{(t,s) \in in(s)} \sum_{(t,k) \in out(t,-s)} I_{(t,s)}^{(t,k)} \frac{\gamma_{tk} f_i(t,k)}{\gamma_{ts}} h(s) \} \\
&\quad \forall \text{ edges } (u,v), u \neq T: \\
&\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}} \pi_s(v) + \sum_{k \in nbr(u,-v)} I_{(u,k)}^{(u,v)} \frac{h(k)}{\gamma_{uv}} \pi_s(k) \\
&\qquad -p_s(u) + p_s(v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \geq 0 \\
&\quad \sum_i \{w_s^-(i) a_i - w_s^+(i) b_i\} \geq 0 \\
&\quad \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i), w_s^+(i), w_s^-(i) \\
&\quad \forall \text{ nodes } u,v: \psi_s(u), \kappa_s(u,v) \geq 0 \\
&\quad p_s(T) = 0, \pi_s(T) = 0
\end{aligned}
\tag{6.12}
$$

6.6.2 All Pair Case

This section presents the derivation of an LP model to compute the oblivious ratio for a multihop wireless network when approximate knowledge of traffic demand is known. Suppose that the traffic demand d_{ij} is within the range $[a_{ij}, b_{ij}]$. Without the restriction OPTU(**tm**) = 1, the master LP is:

$$
\begin{aligned}
&\min_{r,f,d} r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \alpha > 0, \forall \text{ nodes } s: \\
&\quad \forall \text{ TMs } \mathbf{tm} \text{ with OPTU}(\mathbf{tm}) = \alpha, \text{ and } \forall i,j \ a_{ij} \leq d_{ij} \leq b_{ij}: \\
&\qquad \sum_{i,j} \text{energy}_s(i,j)/pow_0(s) \leq r\alpha \\
&\qquad \text{Constraints (2.6) and (5.9).}
\end{aligned}
\tag{6.13}
$$

Since the oblivious ratio r is invariant with respect to the scaling of traffic demand, we can consider a scaled TM $\mathbf{tm}' = \lambda \mathbf{tm}$. With $\lambda = 1/\text{OPTU}(\mathbf{tm})$, we have $\text{OPTU}(\mathbf{tm}') = 1$. Under these conditions, the master LP is:

$$
\begin{aligned}
&\min_{r,f,d} r \\
&\mathbf{f} \text{ is a routing} \\
&\forall \text{ nodes } s, \forall \text{ TMs } \mathbf{tm} \text{ with } \lambda > 0 \text{ such that}: \\
&\quad \text{TMs } \mathbf{tm} \text{ with OPTU}(\mathbf{tm}) = 1 \text{ and } \lambda a_{ij} \leq d_{ij} \leq \lambda b_{ij}: \\
&\qquad \sum_{i,j} \text{energy}_s(i,j)/pow_0(s) \leq r \\
&\qquad \text{Constraints (2.6) and (5.9).}
\end{aligned}
\tag{6.14}
$$

The constraints that satisfy the requirement that traffic matrices can be routed with maximum energy utilization of 1 can be derived. When there is the range restriction of the traffic matrix, the constraint $\lambda a_{ij} \le d_{ij} \le \lambda b_{ij}$ needs to be added. With $g_i(u,v) = \sum_j g_{ij}(u,v)$, the formulation can be simplified. The slave LP for node s is thus,

$$
\begin{array}{ll}
\max_{g,d,\lambda} \frac{1}{pow_0(s)}\{\sum_{i,j}\sum_{(s,t)\in out(s)} \gamma_{st} d_{ij} f_{ij}(s,t) tx(s,t) & \\
\quad +\sum_{i,j}\sum_{(t,s)\in in(s)} d_{ij} f_{ij}(t,s) r(s) & \\
\quad +\sum_{i,j}\sum_{(t,s)\in in(s)}\sum_{u\in nbr(t,-s)} I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} d_{ij} f_{ij}(t,u)}{\gamma_{ts}} h(s)\} & \\
\forall \text{ pairs } i \to j : & \Leftarrow p_s(i,j) \\
\quad \sum_{(j,v)\in out(j)} g_i(j,v) - \sum_{(u,j)\in in(j)} g_i(u,j) + d_{ij} \le 0 & \\
\forall \text{ nodes } u : & \Leftarrow \pi_s(u) \\
\quad \sum_i \sum_{(u,v)\in out(u)} g_i(u,v) tx(u,v) & \\
\quad +\sum_i \sum_{(v,u)\in in(u)} \frac{g_i(v,u)}{\gamma_{vu}} r(u) & \\
\quad +\sum_i \sum_{(v,u)\in in(u)} \sum_{(v,w)\in out(v,-u)} I_{(v,u)}^{(v,w)} \frac{g_i(v,w)}{\gamma_{vu}} h(u) & \\
\quad \le pow_0(u) & \\
\forall \text{ links } (u,v) : \sum_i g_i(u,v) \le c(u,v) & \Leftarrow \kappa_s(u,v) \\
\forall \text{ nodes } u : & \Leftarrow \psi_s(u) \\
\quad \sum_{(u,v)\in out(u)} \sum_{i,j} \frac{g_{ij}(u,v)}{c(u,v)} + \sum_{(v,u)\in in(u)} \sum_{i,j} \frac{g_{ij}(v,u)}{c(v,u)} \le \beta & \\
\forall \text{ pairs } i \to j : d_{ij} - \lambda b_{ij} \le 0 & \Leftarrow w_s^+(i,j) \\
\forall \text{ pairs } i \to j : -d_{ij} + \lambda a_{ij} \le 0 & \Leftarrow w_s^-(i,j) \\
\forall \text{ nodes } i, \text{ edges } (u,v) : g_i(u,v) \ge 0 & \\
\forall \text{ pairs } i \to j : d_{ij} \ge 0 &
\end{array}
\tag{6.15}
$$

The dual of LP (6.15) is:

$$
\begin{array}{ll}
\min_{\pi,\psi,\kappa,p,w^+,w^-} \sum_u \{\pi_s(u) pow_0(u) + \sum_v \kappa_s(u,v) c(u,v) + \beta \psi_s(u)\} & \\
\forall \text{ pairs } i \to j : & \Leftarrow d_{ij} \\
\quad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \ge & \\
\quad \frac{1}{pow_0(s)}\{ \sum_{(s,t)\in out(s)} \gamma_{st} f_{ij}(s,t) tx(s,t) & \\
\quad + \sum_{(t,s)\in in(s)} f_{ij}(t,s) r(s) & \\
\quad + \sum_{(t,s)\in in(s)} \sum_{u\in nbr(t,-s)} I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} f_{ij}(t,u)}{\gamma_{ts}} h(s)\} & \\
\forall \text{ nodes } i, \forall \text{ edges } (u,v) : & \Leftarrow g_i(u,v) \\
\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}} \pi_s(v) + \sum_{k\in nbr(u,-v)} I_{(u,v)}^{(u,k)} \frac{h(k)}{\gamma_{uk}} \pi_s(k) & \\
\quad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \ge 0 & \\
\sum_i \{w_s^-(i,j) a_{i,j} - w_s^+(i,j) b_{i,j}\} \ge 0 & \Leftarrow \lambda \\
\forall \text{ nodes } u,v : \pi_s(u) \ge 0, \psi_s(u) \ge 0, \kappa_s(u,v) \ge 0 & \\
\forall \text{ pairs } i \to j : p_s(i,j) \ge 0, p_s(i,i) = 0 & \\
\forall \text{ pairs } i \to j : w_s^+(i,j) \ge 0, w_s^-(i,j) \ge 0, w_s^+(i,i) = 0, w_s^-(i,i) = 0 &
\end{array}
\tag{6.16}
$$

The correspondence between dual variables and primal constraints follows: $p_s(i,j)$ corresponding to the flow conservation constraint for demand d_{ij}; $\pi_s(u)$ corresponding to the energy constraint for node u; $\kappa_s(u,v)$ corresponding to the link capacity constraint for link (u,v); and $\psi_s(u)$ corresponding to the schedulability constraint for node u. Since there is no conservation constraint for demand d_{ii}, $p_s(i,i) = 0$ is introduce. LP (6.15) has extra range constraints $d_{ij} - \lambda b_{ij} \leq 0$ and $-d_{ij} + \lambda a_{ij} \leq 0$. Consequently LP (6.16) has dual variables $w_s^+(i,j)$ and $w_s^-(i,j)$, which are associated with the range constraints. To help make the derivation of the dual LP (6.16) clearer, leftarrows $\Leftarrow$ are used to indicate correspondence between dual variables and primal constraints in LP (6.15). In dual LP (6.16), leftarrows are used to indicate correspondence between primal variables and dual constraints.

According to the LP duality theory [4], the primal LP and its dual LP have the same optimal values if they exist. That is, LP (6.15) and LP (6.16) are equivalent. Replacing the constraint in the master LP (6.14) with LP (6.16), LP (6.17) is obtained. It has $O(n^3+n^2m)$ variables and $O(n^3+n^2m)$ constraints, where n and m are the numbers of nodes and edges. The LP to compute the oblivious routing with no knowledge of traffic demand can be obtained from LP (6.17).[3]

$$
\begin{array}{l}
\min_{r,f,\pi,\psi,\kappa,p,w^+,w^-} \quad r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s: \\
\quad \sum_u \{\pi_s(u) pow_0(u) + \sum_v \kappa_s(u,v) c(u,v) + \beta \psi_s(u)\} \leq r \\
\quad \forall \text{ pairs } i \to j: \\
\quad\quad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \geq \\
\quad\quad \frac{1}{pow_0(s)} \{ \sum_{(s,t)\in out(s)} \gamma_{st} f_{ij}(s,t) tx(s,t) \\
\quad\quad + \sum_{(t,s)\in in(s)} f_{ij}(t,s) r(s) \\
\quad\quad + \sum_{(t,s)\in in(s)} \sum_{u \in nbr(t,-s)} I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} f_{ij}(t,u)}{\gamma_{ts}} h(s) \} \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \\
\quad\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}} \pi_s(v) + \sum_{k \in nbr(u,-v)} I_{(u,v)}^{(u,k)} \frac{h(k)}{\gamma_{uk}} \pi_s(k) \\
\quad\quad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \geq 0 \\
\quad \sum_i \{ w_s^-(i,j) a_{i,j} - w_s^+(i,j) b_{i,j} \} \geq 0 \\
\quad \forall \text{ nodes } u,v: \pi_s(u) \geq 0, \psi_s(u) \geq 0, \kappa_s(u,v) \geq 0 \\
\quad \forall \text{ pairs } i \to j: p_s(i,j) \geq 0, p_s(i,i) = 0 \\
\quad \forall \text{ pairs } i \to j: w_s^+(i,j) \geq 0, w_s^-(i,j) \geq 0, w_s^+(i,i) = 0, w_s^-(i,i) = 0
\end{array}
\tag{6.17}
$$

6.6.3 Performance Study: Interference-limited and Lossy links

Experiments are set up as discussed in Section 6.2.1. Experiments are conducted for the case where it is interference-limited and links are lossy. The loss ratio of each edge is uniformly set within [0%, 50%]. The schedulability constraints (5.9) with $\beta = \frac{2}{3}$ are included. Table 6.12 shows the results for nine topologies of 81 nodes with a single sink in the center cell and $R_{max} = 15m$. Table 6.13 shows the results for the all-pair case. The oblivious ratios are low, especially when there is approximate knowledge of traffic demand.

[3] As in Section 6.4.1, when there is no knowledge of the traffic demand, i.e., the range is $[0, +\infty]$, the LP to compute the oblivious ratio can be obtained by removing the constraints, $\sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \geq 0$, and the variables $w_s^+(i,j)$ and $w_s^-(i,j)$ representing the range restrictions.

TM		1.5	2.0	3.0	∞
U	min	1.1831	1.3320	1.6252	
	max	1.5835	1.6356	1.9240	
G	min	1.1838	1.3330	1.6279	2.4053
	max	1.5848	1.6382	1.9204	(min)
B	min	1.2378	1.4380	1.6249	
	max	1.5506	1.7279	2.0580	2.7418
R	min	1.2684	1.3895	1.5625	(max)
	max	1.6096	1.6688	1.9251	

Table 6.12: Min and max oblivious ratios over 9 runs 81 nodes with $R_{max} = 15m$, a single sink in the center, interference-limited lossy-links

TM		1.5	2.0	3.0	∞
U	min	1.4250	1.6260	1.7734	
	max	1.7852	1.9657	2.1674	
G	min	1.4265	1.6144	1.7719	2.6742
	max	1.7797	1.9692	2.1729	(min)
B	min	1.3652	1.5301	1.6766	
	max	1.7653	1.9589	2.1521	3.1648
R	min	1.4634	1.6832	1.8934	(max)
	max	1.8424	2.0746	2.2910	

Table 6.13: Min and max oblivious ratios over 8 runs 81 nodes with $R_{max} = 15m$, all-pair case, interference-limited lossy-links

6.7 Implementation Issues

As the performance study has shown, the traffic-oblivious energy-aware routing has excellent theoretical results, i.e., the LP models achieve low oblivious ratios. In the following, several issues in a potential implementation of the routing scheme are discussed.

For a stationary network, the approach of oblivious routing only needs to collect information of topology and initial energy level once. Information about node positions and their connectivity is needed. It is possible to construct the graph of the network with good links, using the techniques in Woo et al. [65] to estimate link quality. The criteria for the goodness of link quality is that its average quality is good and relatively stable. After that, the optimal oblivious routing is computed in a centralized way. For wireless networks where each node has very limited processing power, e.g., wireless sensor networks, the computation of the oblivious routing can be done on a computer first, then the resultant routing is transmitted to a wireless node. A round of message exchanges is needed to set the routing configuration at each node, so that each node knows, for each OD pair, what fraction of traffic to transmit to each neighbor. Once the routing is established, there is no need to collect global network information any more. With only two rounds of message exchanges to establish a routing, the oblivious approach has a low message complexity. Once the routing is established, it is fully distributed. In contrast, the distributed algorithms in [14, 28, 56] and the hierarchical algorithm in [33] need ongoing collection of network information such as the remaining energy level.

The routing computed by the LP model can be implemented in an opportunistic manner, i.e., each node transmits data packets opportunistically to its neighbors according to the fraction specified by the routing. Such an implementation has the potential to combat the fluctuating channel condition in practice. This is achieved by monitoring the outgoing links and choosing the one with good quality at the time of transmission. Recently there are experimental results on link quality estimation, e.g. Woo et al. [65], and interference detection, e.g. Zhou et al. [72]. Their techniques can be exploited to estimate the variation of link quality caused by temporary link failures and interference. The estimate of link quality and the routing fraction determine which link to transmit a packet. This is amenable to a distributed implementation, in which each node only needs to monitor the quality of the neighboring links. Once the fraction of traffic load on each link is satisfied, the energy efficiency is accomplished. In this way, the "single fixed" routing makes "rerouting" transparent. It is desirable that the routing fractions are satisfied in a relatively short time interval, so there will be a tradeoff between using links with good quality and satisfying the routing fractions. The opportunistic implementations of the oblivious routing could help alleviate the impact of channel quality fluctuation.

In an energy-constrained multihop wireless network, when one or several nodes have used up energy, they are disconnected from the network. The network may still be working for a while. Reoptimizition of the routing may be needed. A similar problem, how to optimize the "oblivious restoration" when one or several nodes fail in the scenario of the Internet, is studied in [7]. A similar technique may be used to obtain an optimal oblivious restoration. However, collecting remaining energy capacities consumes energy. Thus, further investigation is needed to justify the benefit of routing reoptimization. A simple approach is, for a node s having flow to the failed node, to bypass the failed node by assigning additional fraction of flow to the other downstream nodes of node s. The adjustment of routing fractions for downstream nodes is determined by the original routing fractions, in an attempt to balance the load. For example, suppose in the single sink case, for origin i, node s has routing fractions $f_i(s,u)$, $f_i(s,v)$ and $f_i(s,w)$ to nodes u, v and w, respectively. When node u fails, node s adjusts routing fractions to v and w as $\alpha(v)f_i(s,v)$ and $\alpha(w)f_i(s,w)$, where $\alpha(x) = 1 + f_i(s,x)/\{f_i(s,v) + f_i(s,w)\}$. This simple approach of detouring around the failed node is amenable to a distributed implementation. It is worth further investigating how to handle failure scenarios.

6.8 Conclusions

Energy efficiency is an important issue in multihop wireless networks with energy concerns. The problem of designing optimal traffic-oblivious energy-aware routing to minimax energy utilization in multihop wireless networks is investigated. Furthermore, schedulability constraints are incorporated when interference is present and reliable transmissions is considered when links are lossy. LP models of polynomial sizes in both the number of variables and the number of constraints with a fairly weak assumption of the traffic demand are designed. With no or approximate knowledge of the traffic demand, the LP models achieve low oblivious ratios. The performance is particularly good when there is a single sink and/or there is relatively accurate knowledge of traffic demands. Table 6.14 presents a brief summary of the performance study.

	single-sink	all-pair
interference-free & lossless links	**very low** (close to 1.0)	low (1.33-2.65)
interference-limited & lossy links	low (1.18-2.74)	low (1.37-3.16)

Table 6.14: Experimental results, the oblivious ratios, for combinations of the scenarios. Oblivious ratio ranges appear in the experiments studied.

A low oblivious ratio may not be achievable for other topologies. It may be lower or higher. The oblivious ratio depends on the topology and the relative energy levels. If the oblivious ratio is acceptably low, the oblivious routing is a competitive option for optimizing energy efficiency. In the studied cases, low oblivious ratios are achieved, especially when approximate knowledge of traffic demands is available.

Several implementation issues are discussed. With several issues to further study and implementation details to fulfill, a first step has been made to design a traffic-oblivious energy-aware routing framework in multihop wireless networks.

Chapter 7

Conclusions and Future Work

Network performance optimization with changing and uncertain traffic demands has been investigated, for both the Internet and wireless networks. In this concluding chapter, this thesis work is summarized, limitations are discussed and future directions are pointed out.

7.1 Summary and Contributions

The Internet. A promising approach for stable and robust intra-domain traffic engineering in changing and uncertain environments has been investigated. MORE, a multipath implementation of demand-oblivious routing [8], has been presented. Several multipath selection methods have been proposed and evaluated, including the method in Chapter 3 which balances oblivious ratio and quality of routing of the oblivious routing in [8]. The performance of MORE has been evaluated by both numerical experiments and simulation. The performance study shows that MORE can obtain a multipath approximation close to the optimal oblivious arc-based routing in [8]. The results also show the excellent performance of MORE under varying traffic demands, link failures and an adversary attack. Its performance is excellent even with a 100% error in traffic estimation.

This work opens the door for a viable deployment of demand-oblivious routing, thus an intra-domain traffic engineering technique robust to changing and uncertain environments.

Wireless networks. Energy efficiency is an important issue in multihop wireless networks with energy concerns. The problem of designing traffic-oblivious energy-aware routing has been investigated to optimize energy utilization in multihop wireless networks. Furthermore, schedulability constraints, e.g. in [30], have been incorporated when interference is present and reliable transmissions have been considered when links are lossy. LP models have been designed, which are of polynomial sizes in both the number of variables and the number of constraints without accurate knowledge of traffic demands. Several implementation issues are discussed. With no or approximate knowledge of traffic demands, the LP models can achieve the performance close to what an oracle can achieve (with oblivious ratios close to 1.0). The performance is particularly good when there is a single sink. This work is a first step in designing a traffic-oblivious energy-aware routing framework in multihop wireless networks.

For both the Internet and wireless networks, the more accurate the knowledge of traffic demands, the lower the oblivious ratio, thus the better the expected network performance, with respect to link utilization in the Internet and energy efficiency in wireless networks.

7.2 Limitations and Future Work

In this section, several limitations of the thesis research are discussed and future directions are pointed out.

Linearity. The performance metrics, link utilization in the Internet and energy utilization in wireless networks, have linear expressions. Moreover, in wireless networks, the concerns with interference and loss are expressed as linear constraints. This makes it possible to achieve a compact linear program for oblivious routing, e.g., as in LP (4.14) and LP (6.17). However, the linearity is not applicable to some performance metrics and some scenarios. An example is when the end-to-end delay is considered, which usually does not have a linear expression. The concept of Wardrop routing is an approach to addressing the concern of end-to-end delay. It is defined in the context of transportation network as follows [64], "The journey times on all the routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route.". A Wardrop routing can be expressed as a convex optimization problem when the traffic demand is known [6]. Another example is, in wireless communications, when the power control is utilized to adjust the energy consumption for transmissions, the performance metric of energy efficiency and the constraints become convex, e.g., [41]. When accurate knowledge of traffic demands is available, concerns with end-to-end delay or power control can be formulated as a convex problem, which is solvable. However, it is not clear if this is still true when there is no accurate knowledge of the traffic demands.

Thus, a promising future study is to answer the question: Can we extend the work of oblivious routing to non-linear problems, in particular, convex optimization problems?

Scalability. Following the work of Applegate and Cohen [8], LP formulations of polynomial sizes, with respect to both the number of variables and the number of constraints, have been obtained for the problems of multipath oblivious routing in the Internet and traffic-oblivious energy-aware routing in wireless networks. However, as evidenced by the empirical study, with the available computation resources (typically at the level of 2-3.5GHz CPU and 1-8G RAM), it is difficult to solve medium-size problems. For example, for LP (4.14), it is difficult to solve a problem for a topology with more than 50 nodes. Several techniques may improve the scalability of the LPs for oblivious routing, including clustering, heuristic approaches and approximation algorithms.

The clustering technique in wireless networking research, e.g. [25, 33], may be useful for this problem, which reduces the computational requirement. First the network is divided into clusters (or zones) [25, 33]. Each cluster is a node in the graph. It is necessary to develop techniques to estimate the energy capacity of a cluster. The cluster head, the node responsible for communicating with other clusters, may change over time for energy efficiency. In this case, the LP models may work on an estimate of the energy capacity of a cluster and an approximation of the distance from a cluster to another cluster. This can solve another problem. In a multihop wireless network, a node may work in either idle or active mode. Alternating between idle and active changes the graph. Thus the LP models can not handle such issues in general. On the other hand, although the structure of a subgraph (cluster) is changing, the graph on the cluster level can be regarded as static. On the cluster level, the LP models are still applicable.

In a heuristic approach, a problem can be solved quickly. However, it usually does not solve the problem exactly, and it may not give a performance guarantee of the quality of the solution. An approximation algorithm can also solve the problem quickly. It guarantees how much the degradation of the quality of the solution would be. It is desirable to investigate fast heuristic approach and efficient approximation algorithms to enhance the computation efficiency of the LP models for the oblivious routing.

Implementation Issues. For the traffic-oblivious energy-aware routing in Chapter 6, LP models have been designed and their performance has been evaluated through numerical experiments. For it to become implementable, several issues need to be further studied as discussed in Section 6.7, including link measurement and estimation to obtain link status, opportunistic packet forwarding to combat with time-varying wireless channels, and fault tolerance to recover from node failures. It is desirable to take advantage of experiences in previous work for link measurement and estimation, e.g., Woo et al. [65], and for interference detection, e.g. Zhou et al. [72], in designing an opportunistic implementation.

The schedulability of the traffic-oblivious energy-aware routing can be guaranteed when interference is present. However, with changing and uncertain traffic demands, how to design the scheduling scheme is an open problem.

A promising future direction is to implement the traffic-oblivious energy-aware routing in wireless sensor networks, where traffic is sporadic and interference is less severe.

Path Selection. Several path selection methods have been proposed and evaluated in Chapter 4 for MORE, a multipath implementation of demand-oblivious routing. As experimental results have shown, a multipath approximation can achieve oblivious ratios close to that achieved by the oblivious routing in [8], which achieves the lowest oblivious ratio for a topology. However, there is still room to further narrow the gap, as shown in

Figure 4.2. Thus, it is desirable to design better path selection methods.

Traffic Burstiness. In the implementation of MORE for the evaluation in Section 4.4.5, the traffic is split at the granularity of flows. However, Internet traffic is bursty, so that there may be a few large flows that dominate the traffic volume. As a consequence, splitting traffic at the flow level may not achieve the desired load balancing. Thus further improvements of MORE may be achieved by splitting traffic at a finer level, e.g., by exploiting the traffic burstiness at the flowlet level as studied recently in [60], where a flowlet is a group of packets arriving at the traffic splitter during a certain time interval.

7.3 Final Remarks

This thesis has advanced the state-of-the-art of research for both the Internet and wireless networks, by designing an efficient and deployable implementation of demand-oblivious routing in the Internet and relaxing the assumption on the a priori knowledge of traffic demands in optimizing energy efficiency in wireless networks. As studied for the Internet in the MORE project and discussed for wireless networks, it is viable to design efficient and deployable protocols based on the optimization approach taken in this thesis. This is particularly interesting for the Internet and wireless sensor networks. I look forward to the proliferation of network protocols based on the approach of oblivious routing, which optimizes network performance with changing and uncertain traffic demands.

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Glossary

CDMA
: Code Division Multiple Access. In CDMA, simultaneous transmissions can be separated using coding theory. 52

competitive ratio
: The competitive ratio measures how far a routing is from the optimal routing for a given traffic matrix. 9

energy utilization
: The rate energy is consumed. 49

interference
: In wireless communications, transmissions may interfere with each other so that signals may be garbled. 51

IS-IS
: Intermediate System to Intermediate System. A popular Internet routing protocol. 6

linear programming
: Linear programming (LP) deals with optimization problems to minimize or maximize a linear objective function subject to linear constraints. 5

link utilization
: The traffic on a link divided by the link capacity. 8

MPLS
: MultiProtocol Label Switching. 6

multihop wireless network
: It is in contrast to the single hop cellular networks where mobile devices are communicable directly to base stations. It may be a wireless ad hoc network, a wireless sensor network, a wireless mesh network, or a wireless network of base stations. 45

oblivious competitive ratio
: Or in short, oblivious ratio. The worst competitive ratio a routing achieves with respect to all traffic matrices. 9

oblivious routing
: The oblivious routing problem is to design a routing that achieves close to the optimal performance, with no or only approximate knowledge of the traffic pattern. 8

OD
: Origin-Destination. The source-destination pair of a flow. 5

OSPF
: Open Shortest Path First Protocol. A popular Internet routing protocol. 6

path dispersion

Path dispersion is concerned with how many paths exist between each OD pair as specified by the routing. 11

path variation

Path variation is concerned with how much the paths between each OD pair differ from the shortest path of the OD pair and how much they differ from each other. 11

quality of routing

Path dispersion and path variation. 11

routing

A routing specifies which route(s) the traffic will flow on and how much traffic a route will accommodate. 1

schedulability

Achievability of a routing in a wireless network. 51

scheduling

In a time-slotted wireless network, a scheduling specifies which time slot(s) a transmitter can be active. 1

TDMA

Time Division Multiple Access. In TDMA, the radio spectrum is divided into time slots; and in each slot, only one node is allowed to either transmit or receive. 52

traffic engineering

Traffic engineering is concerned with performance optimization of operational networks. In general, it encompasses the application of technology and scientific principles to the measurement, modeling, characterization, and control of Internet traffic, and the application of such knowledge and techniques to achieve specific performance objectives. Quoted from [9]. 1

traffic matrix

A traffic matrix (TM) provides the amount of traffic between each OD pair over a certain time interval. 5